SOCIAL AND BEHAVIORAL DOMAINS IN ACUTE CARE ELECTRONIC HEALTH RECORDS: BARRIERS, FACILITATORS, RELEVANCE, AND VALUE

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DEDICATION

In fond memory of Dr. James Kakuda: role model, mentor, fellow data-enthusiast, friend.

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This dissertation is the byproduct of many late nights, a supportive family, and a multitude of inspirational leaders.

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ABSTRACT

Social and Behavioral Determinants (SBD) are defined as environmental, financial, or psychosocial factors that impact the health of individuals and communities. There is increasing awareness that SBD affects health in a more profound way than access to (and quality of) medical services (Gold et al, 2017; Nguyen et al, 2015). Understanding and applying SBD data can mitigate health iniquities and reduce the burden of chronic disease (Roux et al, 2015). Despite this, SBD measures are infrequently and inconsistently documented by healthcare providers (Hripcsak, Forrest, Brennan and Stead, 2015). To address this concern, the Institutes of Medicine (IOM) established a set of 12 SBD data for standardization within Electronic Health Records (EHR; IOM, 2014).

The objective of this dissertation was to provide new evidence about the barriers, facilitators, relevance and value of adding SBD to the EHR in acute care settings. The conceptual model of this dissertation integrates the IOM's 12 recommended SBD in to the commonly-recognized Anderson Model of Healthcare Utilization, which relates the use of health care services to several population characteristics and environmental factors.

In the first study, focus groups were conducted to ascertain hospital employees' perceptions of current and future use of SBD in the EHR. In the second and third studies, two years of de-identified EHR data was collected from two hospital sites on Oahu, Hawai‘i to assess whether the previously-deployed SBD measures of "Physical Activity" and "Social Connection and Social Isolation" could inform the common acute care process measures (length-of-stay and potentially preventable readmissions, respectively). For the study of "Physical Activity" in predicting length-of-stay, a piecewise regression with a breakpoint for time was used. Multiple-logistic regression was used to examine "Social Connection and Isolation" in predicting potentially preventable readmissions.

The results from this dissertation demonstrate that SBD can be incorporated in to acute care quality efforts and social service referrals, subsequently providing improvement to patients' immediate course of care. However, we must continue to conduct feasibility of implementing these measures within the nuances of various acute care workflows. Identifying creative ways to capture SBD, such as patient self-report or natural language processing, may be more optimal mechanisms to obtain trended SBD data, with minimal disruptions to clinical workflows.

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1. INTRODUCTION

Vision of a Community Health Record

There is increasing awareness that personal, social and environmental factors affect health in a more profound way than access to (and quality of) medical services (Gold et al, 2017; Nguyen et al, 2015). Compared to other industrialized nations, the United States spends much less on social services (Thomas-Henkel and Schulman, 2017). Poor health associated with unmet social needs has become a local, state, and national problem (Byhoff et al, 2017).

It is difficult to advocate for social services without data to accurately quantify the need. Accordingly, there is an increasing desire for interoperable data exchange among clinical, public health, and community organizations. Community Health Records, or CHRs, systematically define and collect the broad factors that contribute to an individuals' overall wellbeing (Garg, Boynton, and Dworkin, 2016; King et al, 2016). The discussion around operationalizing CHRs gained substantial momentum after 2010 Affordable Care Act called for community health and health equity to be addressed alongside clinical transformation in health care reform (Van Brunt, 2017).

A mature CHR would allow for the following: 1) directed exchange (e.g., a medical provider sends a referral to a local drug-rehabilitation program) 2) query-based exchange (a politician requests data around the community's homelessness rates) 3) consumer-mediated exchange (e.g., a patient requests the hospital chart from his or her last hip surgery to provide to an out-of-network physical therapist; Marlow et al, 2018). Continuity of this nature would greatly improve decision making and support targeted actions to reduce the burden of chronic disease and improve the health of a community (King et al, 2016). Unfortunately, despite tremendous promise that present-day health information technology (e.g., electronic medical records, personal wearable devices, machine learning, big data, etc) offers to connect and synthesize information to improve personal and community health, effective implementation and use of CHRs remains largely unrealized (Zhang et al, 2017; Philips et al, 2016).

Electronic Health Records – Present State

Electronic Health Records (EHR) from clinical settings have the potential to serve as rich data source to support CHRs by providing low-cost, timely, easily accessible, longitudinal data on large, diverse populations. Considering the 600+ EHR vendors available on the market—and

the fact that that each healthcare system (and arguably each independent hospital) has their own administrative, quality improvement, and research priorities to be addressed within the EHR—standardization and consistent for use at the community-level is an incredibly difficult task (ONC 2016).

In the late 2000s, several federal incentive programs were established in order to facilitate gradual standardization of disparate EHR systems (namely the Health Information Technology for Economic and Clinical Health 'HITECH' Act, and subsequent programs "Meaningful Use" and "Physician Quality Reporting Systems"). In order to obtain for incentive payments, healthcare systems were required demonstrate that their EHR was eligible for "government-certification" by meeting several criteria defined by the Centers for Medicare and Medicaid Services (CMS). Some of these standards included the ability to: generate a standard set of patient demographics, facilitate provider-to-provider communication, and create patient discharge summaries (among others). As of February 2016, 97% of all United States non-federal acute care hospital systems possessed (and 74% of physicians were consistently using) government-certified EHR systems (ONC, 2016).

While this federal stimulus has created an environment conducive to data collection and exchange, there is still a lack of standard documentation for modifiable social and behavioral health determinants (Alder & Stead, 2015). Understanding social and behavioral health determinants are important for providers to understand patients in a more complete context (e.g., understanding financial strain could lead to more informed and realistic courses of care, recognition of domestic abuse could lead to a referral to a community agency that addresses intimate-partner violence). Moreover, systematic collection of this information could inform the growth of specific public health services tailored to a community's specific needs.

Developing Interoperable Data

EHRs were originally developed for billing and communication purposes (without extensive consideration of how it could be used to address the social needs of individuals and communities; Philips et al, 2016; Casey et al, 2016). While diagnoses and disease status are addressed at length in EHRs, the disease etiology (i.e., the fundamental causes of disease), patient engagement, and other relevant social factors are relatively under-documented (Casey et al, 2015). Assuming healthcare systems choose to include non-clinical factors in the EHR, there are few clearly defined standards that would enable data exchange and meta-data analysis nation-

wide (Sweet & Moulaison, 2013). Providers are still largely responsible for independently defining, identifying, and assessing the key social and behavioral determinants of their patients (Adler & Stead, 2015). Commonly, providers will ask patients to provide a narrative account of their social history and circumstances. This information is in-turn documented as free-text within the EHR, making it difficult to address during future visits or synthesize trends at a population level.

IOM Recommendations

To address this concern, the Institutes of Medicine (IOM) established a multidisciplinary committee to define a set of social and behavioral domains (SBD) to be included in future government-based EHR standardization policy and programming (i.e., Meaningful Use, Stage Three). After identifying several "candidate domains," then designated 12 as "high priority" for inclusion in EHR, based on: strength of evidence associating the domain to health, usefulness for clinical and population health research, availability of reliable and valid measures, feasibility, sensitivity, and accessibility (domains were lower priority if the information could be accessed elsewhere) (IOM, 2015). Four of the SBD domains are already commonly collected in the EHR (but were not federally regulated). These include race/ethnicity, tobacco use, alcohol use, and residential address. The remaining eight measures (educational attainment, financial resource strain, stress, depression, physical activity, social isolation, intimate partner violence, and neighborhood median-household income) were recommended as domains that would enhance the documentation of key aspects of a patient's social history.

There was a phased development process for IOM to reach the 12 SBD domains. First, the IOM formed a committee of experts to identify candidate domains. The committee was comprised of social scientists, clinicians, public health experts, and informatics experts (Alder and Stead, 2015). Domains were identified using common public-health frameworks (e.g., Socio-ecological model and life-course model) and final selections for the domains were based on the strength of evidence supporting the association between the domain and health, usefulness of the domain, availability of a reliable and valid measure, feasibility, and sensitivity (IOM, 2014). The group then re-convened to identify standardized measures to associated with each domain and provide examples of inter-sectoral applications for the data. Because the recommendations are so new, and there is no regulatory requirement attached to them, the current literature regarding the application of the IOM SBD domains is still largely comprised of case studies focused on an

application of one of the 12 domains (e.g., Casey et al, 2015; Paul et al, 2015) or on surveys that captured SBD measures outside of the EHR (e.g., Stopford, Winkley & Kirsty, 2013; Prather et al, 2017).

Because these recommendations are fairly recent, there are some gaps in the literature. First, it is unknown how are these recommendations received among frontline clinical staff. Greg, Boynton-Jarett, and Dworkin identified several potential barriers to provider buy-in on collecting SBD data in their 2016 article, "Avoiding the Unintended Consequences of Screening for Social Determinants of Health." For example, providers may feel burdened by the sensitive information included in these domains. There is legitimate ethical concern that the issues identified through SBD screening may extend beyond the scope of clinical care and cause unintended harm (e.g., absence of appropriate social services, damage to the patient-physician relationship, etc).

SBD in Primary Care Settings

The IOM focused its recommendations on primary care. Despite growing attention on these measures, few ambulatory care settings reported implementing systematic SBD screenings, standardized workflows were not available or accessible in commercial EHR systems (Alder & Stead, 2015; Chung et al, 2016). Accordingly, these organizations were faced with the logistical burden of creating custom implementations to include these measures. Several facilities began their efforts by creating screening tool via static PDF, which defeated the end-goal of interoperability (LaForge et al, 2018).

A 2017 study by Gold et al looked at how 27 different community health centers (CHCs) implemented the SBD recommendations from IOM. The broad implementation was made possible by a national coalition that serves CHC-organizations. The coalition created the "Protocol for responding to and Assessing Patient Assets, Risks, and Experiences (PREPARE). Process to develop electronic data capture tools to support the IOM recommendations took 10 months. Moreover, the study found that despite IOM's prescriptive workflow recommendations, there was variation in how the measures were implemented. At the CHC's included in the study, the SBD information was collected via clinicians, front desk staff, community health workers, or self-reported by patients. Clinicians at the community health centers would often transfer the responsibility of SBD data collection to another team member and ignore advisory alerts to collect the information (Gold et al, 2017).

Another recent study by LaForge et al (2018) identified six different organizations that developed processes for measuring social determinants of health. In this study, one of the common challenges was that customization of the IOM measures was the norm. For example, if one of the domains was already addressed within the workflow, the original measure was retained (rather than opting to standardize to IOM's recommendations). Organizations also took liberties to develop more detailed or precise questions depending on their independent community needs. The authors highlighted tension between needing freedom to tailor SBD to specific communities without compromising interoperability. Finally, LaForge et al (2018) noted that an organization's capacity to implement SBD screening was directly related to the organizational capacity to build and maintain EHR tools.

Purpose of Study - SBD in Acute Care Settings

The purpose of this study is to understand the barriers, facilitators, relevance and value of SBD in acute care settings. Little is known about how acute care health systems are developing tools to identify and address patients' social determinants of health (LaForge et al, 2018). Second, there are few recommendations about how these measures should be implemented, particularly in the inpatient setting (Hripcsack et al, 2015; Adler & Stead, 2015; Shortell, Washington, and Baxter, 2009; Pinto et al, 2016). This is highly problematic because un- or under-insured populations—those more vulnerable to health disparities—largely rely on emergency departments or hospitals rather than primary care for their medical services (Kangovi et al, 2013).

Community Partners

For my dissertation, I partnered with Hawai‘i Pacific Health (HPH) in order to assess SBD use and applications within the acute care setting. HPH is a non-profit health care collaborative comprised four acute care hospital facilities and more than 50 primary care clinic locations in the state of Hawai‘i. I am currently employed as a project manager at HPH, and I have developed strong relationships with several departments that will be essential to the success of this project, including: quality improvement, patient experience, information technology, and hospital operations (at least two clinical partners at each hospital facility). My primary role at HPH has been to work among these departments to establish process-improvement interventions to decrease the average length of stay (LOS) at our hospital facilities. For my dissertation, I build

on my previously existing workplace relationships and leverage skills taught in the Public Health Doctoral Program to: 1) assess the long-term effectiveness of these efforts to integrate SBD into the EHR and 2) publish translational research that encourages other administrators to adopt sustainable interventions at their respective facilities.

HPH is considered an "early adopter" of EHR technology. In 2010, HPH became one of the first hospital systems in the nation to be awarded the Healthcare Information Systems Society (HIMSS) Stage 7 Certification. Presently, only about 4.2% of healthcare systems have been awarded this designation (HIMSS, 2015). In order to have this certification, organizations must have an EHR that is fully integrated across inpatient, outpatient, and ancillary settings and possess data-mining processes to capture and analyze data internally for quality improvement purposes. In 2012, and again in 2016, HPH won the Davie's Enterprise Award which spotlighted the organization's population health disease registries and data-driven quality improvement processes, suggesting that the organization is receptive to and prepared for this type of SBD research (HIMSS, 2012; Lofstrom, Wagner, and Roberts, 2016).

Research in the Local Context

While Hawai‘i Pacific Health is considered to be an "early adopter" of a government-certified EHR, the adoption-rates for the entire state of Hawai‘i falls about 10% behind the national average (King, et al 2014; Heisey-Grove & Patel, 2014). Hawai‘i state hospitals are supported by five different competing vendors: Cerner Corporation (44.4% of market share), Epic Systems Corporation (27.8% of market share), MEDITECH (16.6% of market share), Computer Programs and Systems Inc (11.1% of market share), and Alere Analytics (5.6% of market share; ONC, 2016). Moreover, some health care facilities are not even operational on a government-certified EHR that would support such information exchange. Considering the disparate vendor selection—and the fact that each healthcare system (and arguably each independent hospital) has their own administrative, quality improvement, and research priorities to be addressed within the EHR—expanding the prioritization, standardization, and consistent documentation of social and behavioral factors to other healthcare systems in the state could prove to be a difficult task.

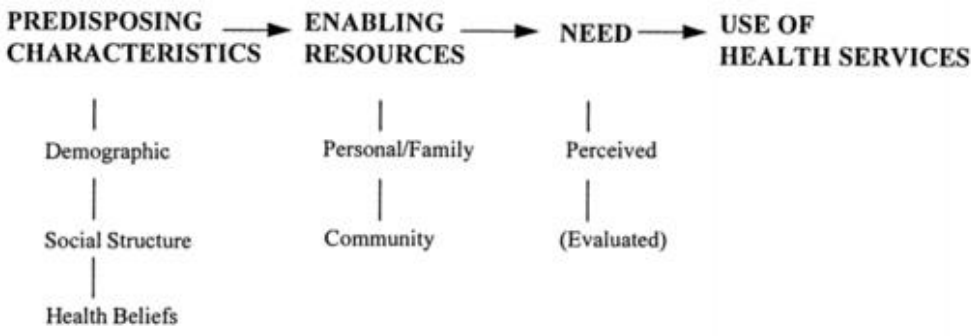
Despite some EHR fragmentation that could limit information exchange, there are some clear advantages to conducting this type of research within the state of Hawai‘i. For example, Hawai‘i has had a very progressive approach to health care, beginning with the "Hawai‘i Prepaid

Health Care Act," which was enacted in June 12, 1974 to set minimum standards of health care benefits for workers – the first legislature of its kind in the nation. This precedence has led to some of the highest rates of coverage and best medical coverage in the nation (Commonwealth Fund, 2017; Levey, 2014). Extensive insurance coverage throughout the state has also enabled unique follow-up care programs for patients, such as survivorship programs to support individuals as they adjust to life after cancer treatment (Levey, 2014). Additionally, the geographic isolation may have forced higher levels of collaboration among the hospitals than what might be seen elsewhere in the United States. Hawai‘i has had databases facilitating information exchange among health care facilities since 1994, through the non-for-profit agency Hawai‘i Health Information Corporation (HHIC). Another repository for data exchange is the Hawai‘i Health Data Warehouse (HHDW), which has been monitoring progress toward state and health national goals since 2009 (Healthy Hawai‘i Initiative, 2014). Evidence-based research that demonstrates the meaning and value of social-behavioral measures in the local context could support future data collection strategies for these efforts, and will be a strong asset as Hawai‘i continues to progress forward with health care reform.

Conceptual Model

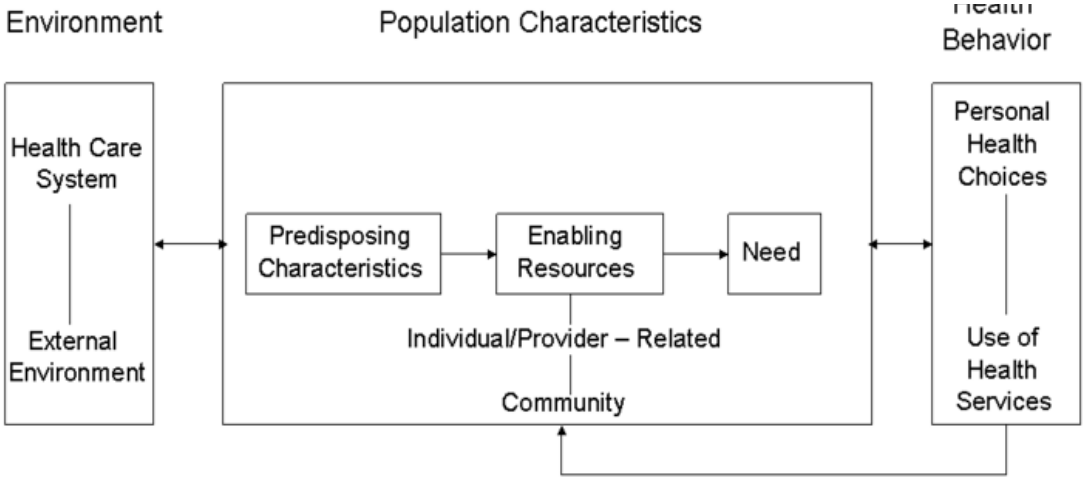
A modified version of the Andersen Model for Healthcare Utilization (AMHU) was used to frame this research. The AMHU model has been widely used and recognized since the 1960s. The contemporary AMHU model is a recursive framework that illustrates the interconnectedness between the independent variables of the environment, population characteristics (predisposing characteristics, enabling resources, and needs) and dependent variables of health outcomes (healthcare utilization or personal health services). The AMHU was originally developed in the late 1960s to: 1) understand what drove healthcare utilization behaviors, 2) measure relative access to healthcare, and 3) inform policy development for equitable healthcare access (Andersen, 1995; see figure 1).

Figure 1.1: Andersen's Initial Behavioral Model for Healthcare Utilization (1960s)



Over the course of several decades, Andersen revisited the model to add elements that addressed access (Is care efficient and effective?) and degree of mutability (Can the predisposing factor be altered?). In the 1970s, the AMHU went through a revision to include elements of "healthcare system" and "consumer satisfaction" to acknowledge how policy reform and individual experiences (e.g., convenience, quality, provider characteristics, etc) influence utilization of healthcare services (Andersen, Smedby, & Anderson 1970). The third phase of the AMHU added "External Environment" and "Personal Health Practices" as elements that impact healthcare utilization. The final iteration of the healthcare utilization model (relative to the initial 1970s model) is more recursive, to acknowledge the dynamic interplay between environment, population health, and health behavior (figure 1.2).

Figure 1.2: Fourth Iteration of healthcare model for Healthcare Utilization (Mid-1990s)

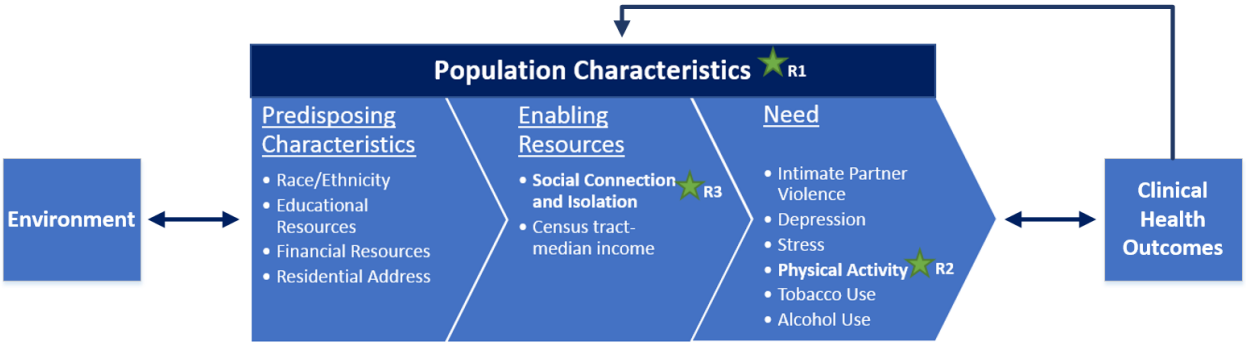


The AMHU is adaptable enough to be used to address healthcare utilization for a variety of different healthcare settings (e.g.: Mental Health Services, Emergency Services), disease-profiles (e.g., diabetes, sickle-cell disease), and demographic cohorts (e.g., homeless populations, immigrants; Gelberg, Andersen, and Leake, 2000; Smith et al, 2005, Babitsch, Gohl, and Lengerke, 2012). The flexibility that the AMHU offers can be both a strength and a weakness, given that there is no best practice for the reference data a researcher should collect in order to conduct an analysis using this framework. In a systematic literature review conducted by Babitsch, Gohl, and Lengerke (2012), some of the variables commonly examined were: Age,

Marital Status, Sex, Education, Employment, Insurance, Access to a Primary Care Provider, and Mental/Physical Health Status (among others). However, even these basic variables were obtained inconsistently. Establishing a standardized set of population characteristics could provide researchers with a more consistent way to apply this model, subsequently providing a more generalizable understanding how these factors influence healthcare utilization patterns.

If sucessfully implemented, the 12 social and behavioral domains recently recommended by the Institute of Medicine (IOM; 2014) could serve as easily-accessible, foundational metrics for future healthcare utilization research that employs the Andersen Model. The twelve measures are as follows: Race/Ethnicity, Educational Resources, Financial Resources, Residential Address, Social Connection and Isolation, Census tract-median income, Intimate Partner Violence, Depression, Stress, Physical Activity, and Tobacco Use. For the development of the IOM measures, these domains were categorized as either: Sociodemographic, Psychological, Behavioral, Relational, or Community Domains. For this dissertation, the IOM measures were re-categorized them as either "predisposing characteristics," "enabling resources," or "need" in order to seamlessly integrate them within the AMHU (figure 1.3)

Figure 1.3: IOM SBD Domains serving as a foundation for the Andersen Model for Healthcare Utilization



Research Questions

This research contributes new information to contemporary public health and health care administration literature by investigating the barriers, facilitators, relevance, and value of adding SBD to the EHR in acute care settings. Three studies were conducted to examine this concept. The three corresponding research questions are as follows:

- What are providers' perceived barriers and facilitators to the adoption of SBD measures in the EHR?
- Does including physical activity measures to the EHR lead to decreased length of stay?

- What is the predictive value of "Social Connection and Social Isolation" on hospital readmission?

These studies set essential precedence for healthcare systems as they adapt to volume- to value-based reimbursement. In order to accommodate this shift, healthcare systems will need to have ability to report and intervene on the modifiable risk behaviors that contribute to chronic disease in order to have a preventative approach to individual health and more effectively manage population health (Barrett et al, 2013; Estabrooks et al, 2012). Currently, there are very few robust, quantitative studies demonstrating the how these domains can be used to inform and improve patient care (IOM, 2014; Alder & Stead, 2015). Without this, healthcare administrators may be hesitant to invest in the initial costs (e.g., Information Technology resources, staff training time, etc.) required to make the EHR changes (IOM, 2014).

There are two additional gaps that the current in the current SBD/EHR literature that this dissertation attempts to address. First, there are few studies which examine providers' perception of and operationalization strategies for socially-complex domains. It is critical that front-line staff find this information both approachable and valuable, because they are the ones ultimately responsible for prioritizing and enforcing the consistent documentation of these measures. Second, the SBD research that is available primarily focuses on the outpatient setting. This is highly problematic because un- or under-insured populations—those more vulnerable to health disparities—largely rely on emergency departments or hospitals rather than primary care for their medical services (Kangovi et al, 2013).

Study 1: Providers' perceived barriers and facilitators for adoption of SBD measures.

Although, intuitively, clinical care and public health should be interconnected sectors, they have historically operated independently. This division exists because these fields have two distinct professional identities wherein one is focused on the treatment of individual patients and the other is focused on the external factors that influence the health of the community (Roux et al, 2015). SBD measures have great promise to generate both multidisciplinary conversations within academia and interoperability among health, community, and government services. However, it is unclear if these measures are universally understood by the providers collecting

them, or if the providers document this information with these future (broad, non-clinical) applications in mind.

As the healthcare systems assess the feasibility of universal EHR integration for SBD domains, it will be important to understand how providers feel about capturing the information. For example, if clinicians think these measures ask patients for unnecessarily intrusive information, there is a high likelihood that this data will be inaccurate and incomplete. It is critical that front-line staff find this information both approachable and valuable, because they will be the ones ultimately responsible for prioritizing and enforcing the consistent documentation of these measures in the EHR.

Research question one, "*What are providers' perceived barriers and facilitators to the adoption of SBD measures in the EHR?"* examines whether there are any user-specific concerns about capturing SBD information about during a patient's course of care. For this study, 4-6 focus groups were conducted with clinical providers use SBD domain documentation fields as a part of their daily roles and responsibilities. Structured questions were asked to ascertain perceived barriers and facilitators to the adoption and implementation process. This study addresses a critical gap in the literature by examining frontline staff perceptions about SBD measures and then identifying barriers or facilitators that are unique to SBD/EHR implementations in acute care settings. Pre-existing literature focuses on EHR adoption and implementation, but there is limited information around the specific attitudes around SBD.

Individuals who regularly engage with the "physical activity" or "social isolation and social connection" measures at HPH (Floor Nurses and Case Managers, respectively) were asked to participate in the study. To gather participants, a convenience sampling of nursing and case manager leadership from Pali Momi Medical Center and Straub Clinic and Hospital (two urban hospitals on Oahu) was completed. My central hypothesis is that *"identification of actionable ways to use the data during the course of care"* will serve as a facilitator for SBD adoption. Conversely, I hypothesize *"social-complexity and high sensitivity of the SBD questions"* (e.g., depression and stress level, sexual orientation, intimate partner violence, financial resources, etc) will serve as a barrier for providers that do not have extensive social work or behavioral health training.

While SBD recommendations are available, there is very little information about how to make this complex standardization a reality. This research is intended to provide policy-makers

and hospital administrators with additional practical, user-end specificity about what is required for a successful SBD implementation process.

Study 2: Impact of adding physical activity measures to an inpatient EHR Screen

Research question two is, *"Does including physical activity measures to the EHR lead to improved clinical outcomes?"* While "physical activity" is one of the IOM SBD Domains, the typical metrics of physical activity measurement are not really appropriate for individuals who have had a recent medical event that has the potential to limit their ability to exercise. This study contributes new knowledge by assessing the effectiveness of physical activity measures that are tailored for this population.

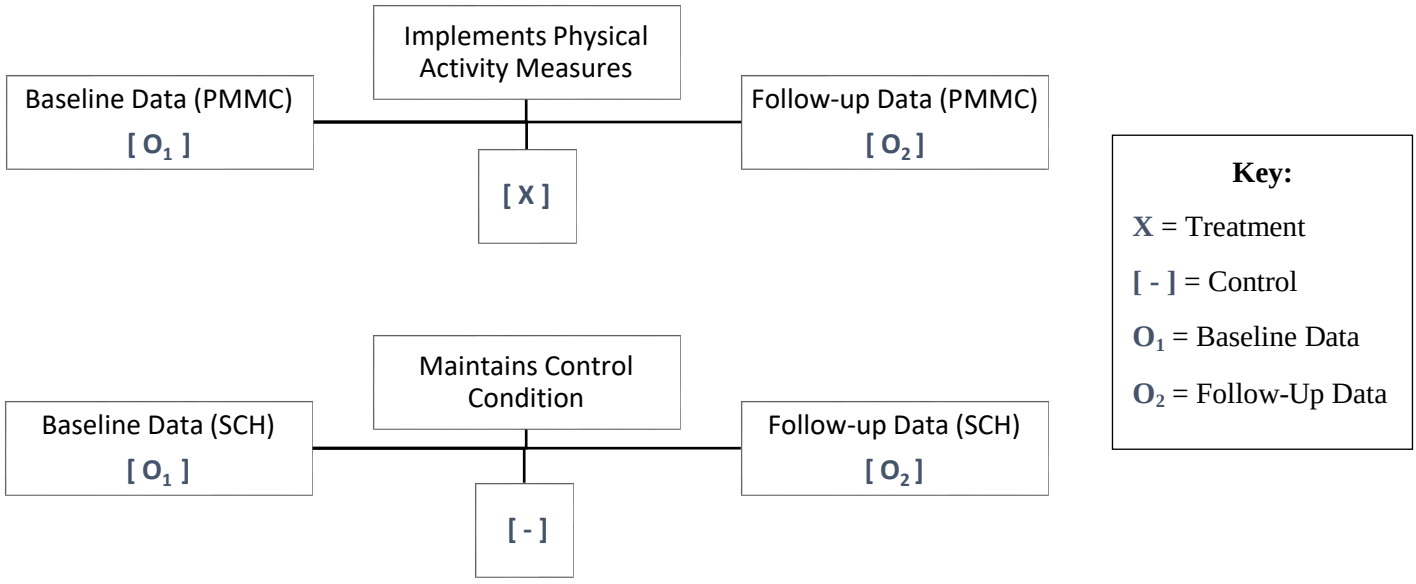
Frequent mobilization while hospitalized has several physical, psychological and social benefits for patients, including fewer post-operative complications, increased levels of patient autonomy and decreased stress and anxiety among caregivers (Kalish, Lee, & Dabney). It also prevents functional decline due to hospitalization in adults ages 65 and older, which is important for local acute care facilities; older adults represent 15.6% of Hawai'i's state population, compared to 13.0% in the United States as a whole (Pashikanti & Von, 2012; Hawai'i Health Matters, 2013).

Studies have found that, despite recommendations for regular physical activity even among the acutely ill, hospitalized patients spend 75-83% of their wakeful hours lying in bed (Kuys, Dolecka, and Guard, 2011; Brown, 2009). To further understand the baseline levels of inpatient ambulation within HPH, summer interns conducted an informal survey of patient activity among hospitalized adults (excluding the labor and delivery patients). Despite having a different sample size and timeframe, our findings at HPH were very similar to the outcomes observed in the literature in other locations (Kuys, Dolecka and Guard, 2011; Brown, 2009). Patients were lying or sitting in bed for 76% of the 738 encounters observed. Accordingly, improving inpatient mobility became an organizational priority at HPH during the summer of 2015.

The result was a naturally occurring experiment at HPH that provided data to inform the second study of this dissertation. In order to increase inpatient mobility and ultimately improve patient outcomes, one hospital decided to focus on reliably collecting several physical activity measures: 1) for physical activity levels at home (the IOM recommendation), 2) baseline

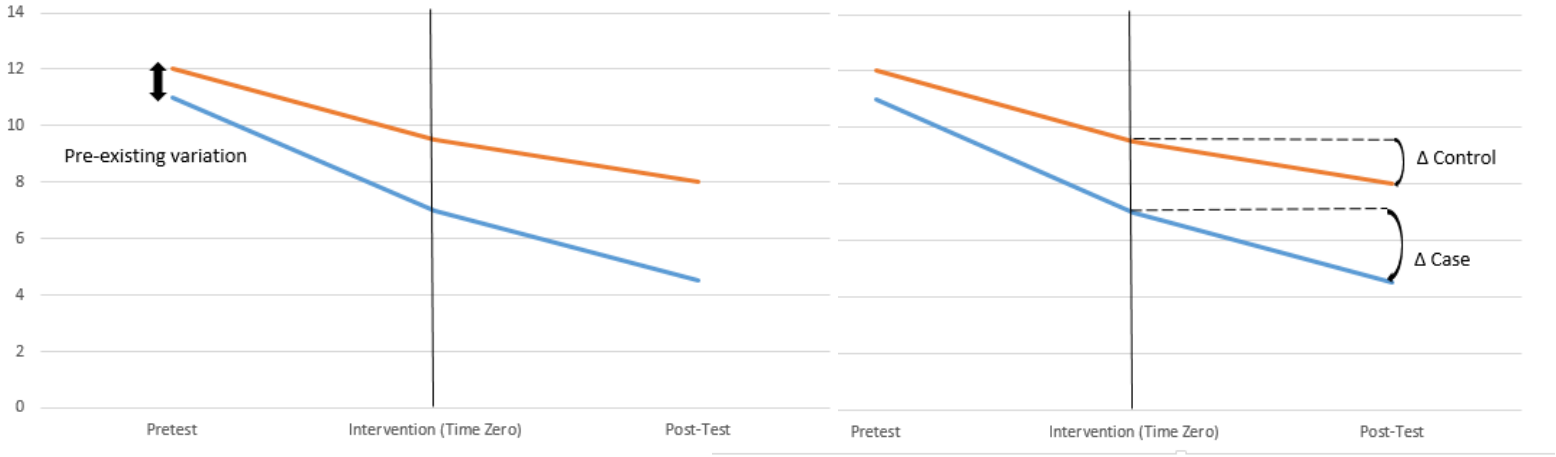
mobility status upon hospital admission (an important distinction for populations, like those who have a stroke prior to admission), 3) frequency of mobilization per day while hospitalized, and 4) mobility status at discharge. In addition to making these changes, hospital operations managers developed physical activity education for providers (to encourage documentation) and patient families (to encourage continued activity post-hospitalization). One hospital made these changes March 1st, 2016. However, it has yet to be implemented at other facilities. The staggered implementation makes this effort a perfect candidate for a quasi-experimental study, where hospital facility serves as a non-random assignment to an intervention and non-intervention conditions for non-equivalent groups (figure 1.4).

Figure 1.4: Quasi-Experimental Design – Pretest Posttest Nonequivalent groups



For this study, 2 years of EHR data was collected from the case and control facilities (PMMC and SMC, respectively). A piecewise regression with breakpoint for time was used to complete this study. This model assumes there will be a distinct difference in the delta between the two facility CMI-Adjusted ALOS outcomes following the intervention (Figure 1.5). The hypothesis of this study is that the case site (with the inpatient mobility intervention) will have a greater decrease in CMI-Adjusted ALOS compared to the control site while controlling for other factors.

Figure 1.5: Desired Trends for Outcome Variables (Overall Decrease; Study 2)



Inpatient mobilization has been identified in the peer-review literature as one of the most frequently missed elements of nursing care, perhaps due to the normative expectation that bedrest is the best course of care during hospitalizations (King, 2012). If successful, this study will provide administrators with a strategy to document and provide evidence to address the excessive inactivity that occurs during hospitalizations, subsequently improving patient care. Integrating SBD metrics into on-going quality improvement efforts may be an unobtrusive and creative way to integrate some of these measures into the EHR.

Additionally, this study provides additional specificity for a vulnerable population within IOM's "Physical Activity Domain": those who have limited mobility. The domain was designed to understand whether individuals were participating in healthy behaviors. However, a deeper understanding of physical mobility could inform everything from an individual's need for enhanced post-discharge care (at the clinical level) to additional advocacy for universal design for urban planning within a community (at the public health level).

Study 3: Predictive value of "Social Connection and Social Isolation" on readmission outcomes

Considerable theoretical and empirical work has focused on how social relationships (such has marital, family, or community connections) influence behavior (IOM, 2014). Research indicates a lack of social relationships is associated with several pre-cursors to chronic disease,

including high blood pressure, high cholesterol, and high blood sugar (Holt-Lunstad, Smith, & Layton, 2010). Several studies have measured clinical outcomes for individuals with cancer or chronic disease, but the "social connection and isolation" data was collected outside of the EHR via self-reported survey (Stopford, Winkley & Kirsty, 2013; Thompson et al, 2016). My analysis will help examine whether a social isolation currently captured in the EHR (i.e., whether individuals "live alone") has predictive value for acute care health outcomes (as very few hospitals have implemented the informatics to support this measure).

As a part of a software upgrade in October of 2015, HPH added a data field for case-managers to begin collecting information on "Social Support at Home." This information is used to identify whether patients needed additional help identifying a care-giver for post-discharge care (the data had immediate, daily application). The field was not originally designed for SBD analysis, but aligns with IOM's recommended measure for "Social Connection and Social Isolation."

Accordingly, research question three is, "What is the predictive value of *"Social Connection and Social Isolation" on readmission outcomes?"* I hypothesize that patients who are identified in the EHR as "living alone" will have an increased likelihood for readmission, because there is no established support-system for follow-up care. This study illustrates how SBD measures can be used to enhance predictive modeling for clinical outcomes that are of immediate interest to the clinical community, subsequently establishing value and precedence for future SBD implementations in the acute care setting.

In order to complete this study, 24 months of retrospective EHR data (October 1, 2015 – September 30, 2017) was collected from two mid-sized hospitals within HPH (Pali Momi Medical Center and Straub Medical Center). The selection criteria for this study was all acute inpatient hospitalizations for individuals 18 years of age and older (estimated ~30,000 hospital encounters). I will examine whether "Social Isolation and Social Connection" have predictive value relative to readmission: as defined by "Hospital Encounters within previous 30 Days (y/n)" (aka: "All-Cause Readmissions") and "Potentially Preventable Readmission (y/n)" calculated through the 3M Risk-Adjusted Algorithm. For Hawai‘i Pacific Health, the baseline rate of "All Cause Readmissions" was 9.5%, or an average of 103 cases per month. The "Potentially Preventable Readmission Rate" is a more rigorous measure, applying to an average of 6.4% of cases, or an average of 70 patients per month. Multiple logistic regression was used to examine

the impact of "Living Alone" against 30-day potentially preventable readmissions, while controlling for several additional clinical, social, and demographic variables (e.g., age, ethnicity, acuity, etc).

Based on previous literature research, I hypothesize poorer outcomes (as measured by higher readmission rate) for patients who are experiencing social isolation and have multiple chronic conditions or a diagnosed mental disorder (Hendrie et al, 2013; Hibbard & Greene, 2013, Cohen-Mansfield et al, 2016). While literature suggests that social isolation can lead to more frequent utilization of health care services, most of the data collected for social isolation is gathered via patient self-report or in an interview type format. This study fills a critical literature gap by examining this measure as documented by a provider in the EHR.

Previous literature for SBD has primarily focused in the outpatient realm. Taken together, these three studies will contribute new information to the literature by providing insight to SBD in the acute care settings. The first study provides provider perspectives on the barriers and facilitators of SBD in acute care EHR. The second and third studies provide examples of how to leverage SBD data that currently exists in the acute care EHR. The final chapter of this dissertation will collate the results and provide implications for policy, practice and future research.

2. STUDY 1

Research Question: What are providers' perceived barriers and facilitators to the adoption of Social Behavioral Domains (SBD) measures in the acute care electronic health record (EHR)?

Abstract

Where previous EHR research has focused on encouraging providers to generally adopt the EHR into their clinical practice, this study provides information about providers' perceived barriers and facilitators for the adoption of SBD measures in the EHR. Specifically, this study fills a critical literature gap by examining how to encourage providers to capture the non-clinical information that (while critical to informing public health policy) might not be perceived as immediately critical to patients' course of care. Focus groups were conducted among nurses and case managers who are expected to document some form of social and behavioral domain (SBD) in the EHR in order to further understand the process, barriers and facilitators to capturing this information. Thematic analysis was used to interpret and synthesize the data. A total of 5 focus groups were conducted. The final sample included a diverse set of participants from two different hospital facilities, some managers and some frontline staff as well as representation from inpatient, emergency department, and operating room settings. While some perceptions and opinions varied by role, there were several salient themes. Participants identified time, mandated reporting, detrimental patient implications, and data integrity as barriers to capturing SBD in the EHR. The participants felt that alternate methods of reporting and closed feedback loops would facilitate SBD data capture in the EHR. The results of this study highlight several nuances in the inpatient, emergency department, and operating room that may impact when and how SBD is captured. Participants also felt that SBD was best understood within the context of a narrative, which suggests the need for continued feasibility research around using natural language processing for the capture of SBD.

Introduction

Despite the increased emphasis on preventative health efforts following the Affordable Care Act of 2010, there is still a major division between the between public and clinical health fields. Namely, it is difficult to generate cross-disciplinary conversations because the field of clinical medicine is often concerned with the treatment of unhealthy individuals and the field of

public health is focused on the factors that cause an individual to be unhealthy (Roux et al, 2015).

The integration of SBD Measures in the EHR is one example of how to bridge the gap and facilitate collaboration between these two sectors. Over the last several years, there has been some policy enacted to support the effort to systematically capture these measures. Legislation from the Health Information Technology for Economic and Clinical Health "HITECH" Act the subsequent "Meaningful Use" hospital and physician reimbursement structure have been able to mandate the collection of patient-self-reported information about tobacco-use and depression indicators. This information is collected by the National Committee for Quality Assurance and recorded in the Healthcare Effectiveness Data and Information Set (HEDIS).

However, researchers who are interested in conducted large-scale EHR data investigations are often frustrated, because the data elements that fall outside of what has been prioritized by Meaningful Use (and other reimbursement-driven programs) are incomplete or unavailable (Glasglow et al, 2012). A lack of standardized measures and inconsistent definitions of what constitutes the scope of "patient health and wellbeing" can severely limit researchers' ability to adequately leverage EHR data for population health surveillance purposes, and leaves a lot of unmet potential for positive change in health policy.

In 2014, the Institutes of Medicine (IOM) published recommendations for 12 social and behavioral domains to be standardized and universally implemented in the EHR. While these recommendations are a great step toward understanding total patient well-being, a lot of questions remain. For example: *How do providers feel about asking patients about this potentially intrusive information? What other barriers exist (logistic or otherwise) to consistently and reliably obtaining this information?*

Literature has identified several key barriers to implementing social and behavioral information into the electronic health record. For example, SBD data is often difficult to quantify. Specifically, it is difficult to determine validity and reliability of self-reported data (Ockene, Reed, and Reiff-Hekking, 2009). Another common barrier is that the information is not actionable and therefore difficult for providers to prioritize (Garg, Boynton-Jarrett, & Dworkin, 2016). This research addresses the gap in user-end provider perspectives on integrating SBD measures in the EHR, by conducting focus groups at a hospital system that has already implemented some of the IOM recommendations. The focus groups examine: 1) the logistical

challenges of adding and consistently documenting SBD in the EHR, 2) the provider-burden imposed by SBD domains, 3) the value and applications of SBD measures once they are in place, and 4) any other common themes that are distinct from the general literature about EHR adoption. The central hypothesis for this study was that "identification of actionable ways to use the data during the course of care" will serve as a facilitator for SBD adoption. Conversely, "social-complexity and high sensitivity of the SBD questions" (e.g., depression and stress level, sexual orientation, intimate partner violence, financial resources, etc.) will serve as a barrier for providers that do not have extensive social work or behavioral health training.

Methods

Participants

For this study, focus groups were conducted with the stakeholders who regularly engage with EHR at HPH. Willing participants were recruited via a combination of convenience sampling and snowball sampling. In order to be eligible for the study, participants were required to be: 1) ages 18 and older, 2) a nurse or case manager who engages with the SBD fields of interest, and 3) employed one of the two urban acute care facilities at HPH (Straub Medical Center or Pali Momi Medical Center). As a part of the IRB process, Chief Executive Officers, Chief Operations Officers (COO) and Chief Nursing Executives (CNE) were provided the research protocol and asked for a signature of approval. After all of the hospital-specific approvals were obtained, a follow-up email was sent to the COOs and CNEs at each facility to ask permission to announce the study at an upcoming safety huddle. Safety huddles are held at each facility daily, with leadership from case management and nursing (as well as several other operational areas). Interested leadership was asked to sign-up and participate. The members of leadership were asked to help identify frontline staff and help identify hours when focus groups could be held.

Nurses and case managers were selected as participants for a number of reasons. First, these groups directly engage with the SBD measures that currently exist at HPH. HPH's "Physical Activity" measures are captured by nursing staff, and have been implemented at the various sites between 2016 and 2018 (beginning in the ICU, and moving to other departments). The "Social Isolation" measure was implemented in October 2015 as a part of an EHR module upgrade for Case Managers. Both nurses and case managers are also responsible for documenting some of the more common SBD measures, including residential address,

race/ethnicity, and tobacco and alcohol use. When possible, efforts were made to conduct focus groups with leadership and frontline staff separately, in order to elicit honest responses among and within peer groups.

Procedures

This study was approved by the Western IRB (see Appendix 1). Each participant was given a waiver for consent and individuals were asked permission for recording of the focus group (see Appendix 2). Participants were given the option to opt-out of the study at any point in time. Audio was transcribed verbatim and individuals were assigned pseudonyms in the documents to further protect participants' identities. De-identified transcripts were retained on an encrypted thumb drive and analyzed for emergent themes.

Focus Group Questions

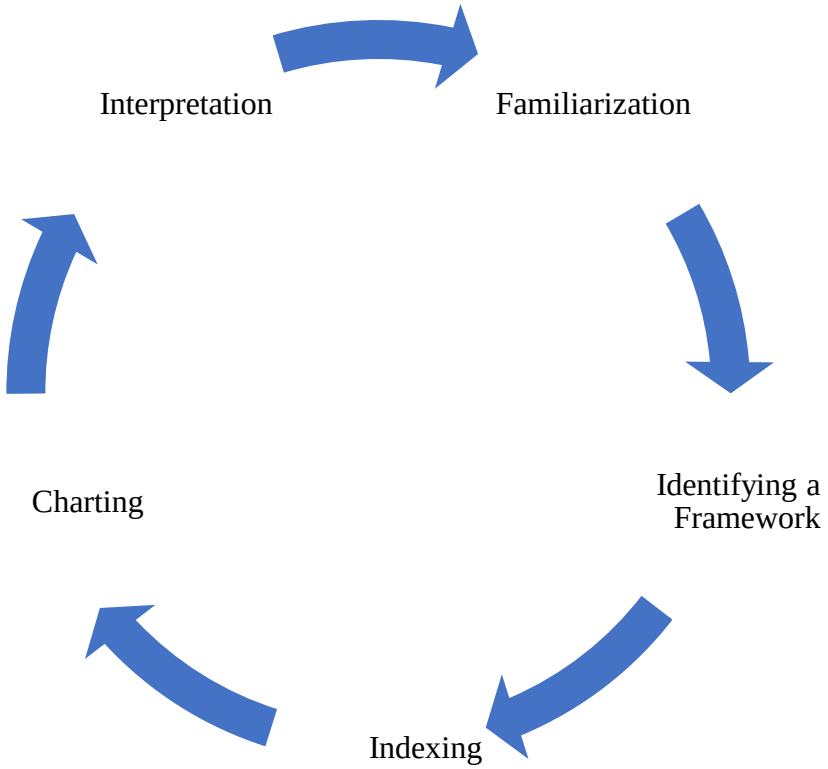
Interview questions were created based on findings in the literature and a pilot study conducted in spring of 2015 (see Appendix 4 for the complete list of questions). The focus groups began with reading a script that disclosed my role as a project manager for Hawaii Pacific Health and defined that this work is being academic in nature (see Appendix 3). Focus groups were asked to provide background on their current approach to document social history. The concept of "Social and Behavioral Domains" was aided by a hand-out that defined the 12 SBD measures identified by the IOM. Participants were asked to provide information about their current roles within HPH and how many years they were in health care.

To gain information about general perceptions about SBD, participants were asked to define social history followed by a question about how the social and behavioral domains are used today. Next, participants were asked about what SBD measures do not exist presently that would be meaningful in their day-to-day work. Participants were asked to provide information about what challenges they expected with the feasibility of getting this information to the EHR. A total of 5 focus groups were conducted.

Qualitative Analysis

A thematic analysis was used to complete this study. Thematic analysis is a stepwise framework process initially described by Ritchie and Spencer (1994), which involves five highly interconnected processes: "familiarization, identifying a thematic framework, indexing, charting, and interpretation" (Raibee, 2004). This approach allows themes to develop both from research questions and from narratives provided by the study participants (see figure 2.1).

Figure 2.1: Ritchie and Spencer's Framework for Thematic Analysis



First, the focus groups were completed. Once the data collection was complete, transcription was used to gain familiarity with the data. During the focus groups and while reading through the transcriptions, observational notes were taken to mark ideas, concepts or categories that could inform the development of a thematic framework. After themes were established, themes were indexed to detail to sort specific quotes and make comparisons between cases. In the charting phase, quotes were lifted from their original context and rearranged to make interrelationships more apparent. Finally, these ideas were synthesized during the interpretation phase.

Results

Characteristics of the Sample

A total of five focus groups were completed (n=20). The sample was diverse. The participants included a mix of leaders (n=8) and frontline staff (n=12). There was even representation of both facilities (PMMC, n=6; SMC, n=14). There was a mix of case managers (n=5) and nurses (n=15).There was also a mixture of individuals from the emergency department (n=4), operating room (n=4) and the inpatient setting (n=12)[1]. An individual's role within the organization shaped the level of engagement with (and interest in) social and behavioral domains in several ways.

Leaders within HPH felt they would be interested in the aggregate reporting outcomes of SBD collection. The leaders were able to give examples of how they would use the data if it were provided. For example, reports could be used to support staffing decisions, program development, and community outreach events. Two of the nursing leaders mentioned how the information would be able to inform their personal testimony and involvement with state legislative activity. Leaders quickly identified ways that the data could be used for HPH as an organization to support social needs in-house (e.g., hiring new resources within the hospital facilities) or within the community (e.g., sponsored community events).

Conversely, frontline staff felt that the main way to leverage SBD data was to optimize existing community resources. Frontline staff noted that capturing SBD data in a more formal way was just the first step in a long journey of improved community health. Moreover, frontline staff felt they should be provided something "in return" for capturing the information (e.g., a consistently updated list from the government that provides all of the existing non-profit agencies and the social needs that are addressed; a closed loop message back to the clinician when community agencies address a need identified in the hospital setting, etc). Frontline staff felt that providing SBD data back to community organizations could help ensure consistent year-over-year, which would help provide continuity for referral processes. One ED staff member that SBD data could be used to justify tighter partnerships between the hospitals and community resources (e.g., incentivizing an "on-call" structure for resources that are regularly called upon during late night and early morning hours).

[1] Note: Some managers had responsibility over more than one area (e.g., case management leadership were responsible for both the emergency department and inpatient settings).

Surprisingly, while there are differences in roles and responsibilities, there were few distinct themes between the nurses and case managers. Due to their integral role in discharge planning, case managers more consistently raised concerns about what SBD would hamper placement of the patient in to assistive care (see more detail under Theme 3). However, the concerns about the logistic and operational challenges of capturing SBD seemed to be relatively synonymous between the two roles. This may be because case managers at HPH are trained and licensed RNs; their interactions with, and responses to, EHR changes may be very similar.

Finally, an individual's role within the hospital: whether he or she worked within the emergency department, the operating rooms, or on the inpatient floors, seemed to influence responses to the focus group questions in minor ways. For the individuals in the emergency department, the association between an individual's social need and frequency of emergency department encounters was very evident to providers. Individuals who worked in the emergency department readily acknowledged their responsibility to not only capture the SBD data, but to also provide resources to the patient to meet the need. The individuals who worked in the emergency department focused many of their responses on the SBD measures that pertained to intimate partner violence, stress, and depression. Emergency department (ED) providers have a heightened awareness of those domains because it is not uncommon for patients to be in the ED for treatment from injuries resulting from intimate partner violence or self-harm. Two ED providers noted that "stress" as an SBD, was an important item to assess, but the providers were interested in individuals' stress and agitation in response to trauma (rather than stressors in day-to-day life as the IOM intends). Heightened stress and agitation could influence an individual's course of care within the ED. For example, a patient may respond to medications differently under stress or staff may choose to triage individuals more quickly if they think the individual will act-out in the waiting room.

Participants who worked in the Operating Room (OR) explained the primary interest in SBD was would be to determine whether the proposed surgical intervention was appropriative for the individual's lifestyle. For example, an orthopedic procedure may be performed differently depending on how physically active an individual is or if an individual is homeless an unable to complete the appropriate follow-ups, different accommodations will be made. Accordingly, SBD screening was done at the beginning of (or even prior to) the patient encounter. OR providers

also mentioned that after the surgery they completed different levels of SBD screening depending on whether the patient was subsequently admitted to the inpatient level of care.

Inpatient (IP) providers also screened for SBD at the beginning of their encounters with the patient by completing both the "home assessment" and the "initial nursing assessment." The home assessment is comprised of several questions, including whether patients are independent, whether they have primary caregivers, and whether they use equipment at home. In the initial nursing assessment, factors like homelessness, substance abuse, and alcohol abuse are collected. Even though the information is collected at the beginning of a hospitalization, participants mentioned that they did not use the SBD information until the end of the inpatient stay, to help with discharge planning.

Despite these differences in workflows (and perceptions) among the various groups of participants, there were several salient themes within the focus groups. These themes were sorted in to two different categories: barriers and facilitators to documenting SBD in the EHR.

Barriers to SBD

Theme 1: Not Enough Time

In the focus groups, nurses and case managers both acknowledged that asking SBD questions, or asking SBD questions in too much detail could lead to the patient providing more information than was appropriate or necessary. This raised concerns for a number of reasons. Especially when clinicians had competing priorities, they didn't necessarily have the time to talk through the detail of an individual's life story:

"Yeah. Every day we deal with it…You start opening Pandora's box and it's, 'My mom was abusive 25 years ago and my father was an alcoholic and my grandmother smoked dope' and, you know, it just goes on and on. And 'I have had this many surgeries,' and it's just…we don't have time."

"It's kind of a resource thing, 'cause if you don't have time to be asking nurses to dig deep in to all these little things, and they're gonna end up in the medical record, which is hard to utilize, particularly, the details that are [free text]."

"You've got four patients, two of them are critical, that you're titrating medications on or something. This guy who is demanding they want all kind of stuff, and I want a sandwich, and I

want this. And so they're getting pulled in multiple different directions, and they don't have time to sit down and fill out 30 questions… you've got to keep everything short and sweet."

Theme 2: Responsibility as a Mandatory Reporter/Professional Responsibility

The groups also shared a lot of concern over their role as mandatory reporters.

"*Yeah, and then what is your responsibility now that you have all that information, you know?"*

"And we have to disclose, so as you find out information about somebody's past…if there's violence or, you know, they were a sex offender then of course, we – we may not document it, but we're certainly obligated to disclose that for the safety of where we're placing the patient."

One concern about collecting SBD data was that patients can refuse to accept the resources which are extended to them. A few participants felt that an important item to accompany the IOM questions (which would help define the scope of their professional responsibility) was asking the patient directly whether they would willingly accept the services.

"Maybe a question would be, 'Do you want help?' and if they don't, then fine. We don't have to go through this because it doesn't matter. Then if you do, then we can go through the questions, and we can try to see what we can do."

"I kind of want to see, 'Do you experience any of these?' Next question. 'Do you need any assistance?'"

"It's almost too bad we can't word it in a way like 'You've come here for help.' You're agreeing for us to help with these things."

The concept of 'patients refusing additional assistance for social needs' was particularly burdensome for cases dealing with domestic violence or homelessness:

"And that in and of itself is a real ethical problem. Nurses struggle with that all the time. Because they wanna save that person. That person don't wanna be saved…but it's one of those things where you wanna try to do something but you can't. It's up to that person to initiate all of that stuff."

"Sometimes patients are offered all of these [resources] and they're like, "I'd rather do drugs on the street."

On the other end of the spectrum, participants were concerned about how to handle screening for SBD when social services are unavailable to address the need.

"*If it's during the day Monday through Friday, very easy. But the ER's operating all the time, and overnight is where a lot of the social problems start happening…so getting agencies outside [the hospital] to support…is always an infinite barrier."*

"We don't have the psychologists and the funding and everything else that we would need to take care of a lot of these. I think it's good that we get the data, but then what do we do with it?"

There were also several scenarios identified where the screening for sensitive SBD seemed inappropriate to participants:

"*…For example, podiatry…A guy's just trying to figure out what's the best golf shoe that he needs to use now that he's turned 58. And then the RN gets to this domestic violence question."*

""RN's [are] mandatory reporters, right? We gotta step up… and all of the sudden this form forces me to ask this question, and now it's like 'Hey, he was just looking for what kind of SPF he needs to use for when he goes down to Barbados next week.'"

Theme 3: Detrimental Implications to the Patient

Because the medical record is a legal and shared document, participants expressed concerns that documenting SBD would have potentially detrimental implications for the patient. One major logistical concern was that documenting SBD may impact patient placement in to post-discharge services (like a skilled nursing facility).

Participant 1: "*And unfortunately, once you document all that stuff on the record, we share that information with our post-acute providers, they have access to the same notes. They're gonna look at it and say 'Oh my gosh. I don't want this type of person in my house' because it's a vulnerable population in the nursing facilities, right? So that's what we're really careful about what information we're pulling."*

Participant 2: *"'cause it could have an effect on whether somebody takes a patient. Absolutely…and what happened to somebody socially 20 years ago doesn't really matter now, but it could to a home operator who says, I don't like that. I don't care if it's 20 years ago. And now, we're having difficulty placing the patient."*

Participants also expressed concerns about the IOM measure of median census tract income being documented in the electronic health record. The potential consequences they were 1) that the patient may be offended or 2) that there is a risk that the information may be stolen. As seen in this exchange between two focus group respondents:

Participant 1: *...I've never heard of needing household income. No, we don't do that, and why would we?*

Participant 2: *... I mean, I think it's useful information to know…household income, but as a patient, I'd be like, um...*

Participant 1: *Why are you asking me that? Yeah.*

Participant 2: *Especially with people, like their health information can be stolen...*

Participant 1: *I would be offended if somebody asked me. I'm sorry. As a patient, I would be offended.*

A third example of a "detrimental impact to the patient" was also shared, specifically around the intimate partner violence concern. The current practice for HPH is to print and provide after visit summaries (AVS) to patients. The AVS is often where providers will share information about community resources available to the patient. An ED participant raised a very practical concern over the AVS sheet landing in the hands of an abusive partner:

"So the doc actually printed up two different sets of AVSs, right? One that talked about some basic medical stuff, and the other one that had all the resources in it for her. And he just told her you've gotta keep this from him. You can't let him find this."

Another interesting theme that came up was how having SBD information discreetly available might introduce biases that may cause providers to overlook issues. Several participants explained that documenting these SBD may "taint" the way a provider is viewing the individual due to personal biases or stereotypes.

"And some of them may approach it with their own filters in place….Which is a liability because you can miss something very serious in somebody…Doesn't mean that it won't happen."

This concern about bias was frequently discussed when screening for educational-levels. Moreover, documenting education-level in a discrete way may cause providers to miss critical questions around patients' understanding or health literacy.

"[If] they have a high school education level versus a graduate level are we biasing it already? Okay, this person doesn't need as much education or support or this patient needs more…"

"It's like if [I] were to give birth. I want an OB nurse. I know nothing about it…just because I'm a nurse doesn't mean I know everything."

Participants felt that the education level data didn't provide value-add because common practice is for all patient education materials to be brought to fifth-grade reading level, regardless of and individuals' education level. One participant mentioned that they needed more specificity out of the measure to ensure patient safety:

"*I don't [want] the education or education level, but their understanding of 'Are they on any medicines and do they know why?' 'Do they have diabetes or cardiac disease?' 'Do they understand that?'"*

Theme 4: The integrity of SBD data is questionable

Several of the participants felt that SBD data that was discretely captured was un-reliable. Several noted that there would be inconsistencies between what was captured discretely via survey versus what could be captured by an individual who was trained to interview for those sensitive topics (i.e., Social Work). Several of the interviewers also thought the information proposed by IOM was better to surface in the midst of a free-text narrative than discrete documentation. A measure of stress had very different context for an ED Nurse Manager than it may for a primary care provider. For example, agitation in an emergency department could be circumstantial and not a chronic condition for that individual. For ED providers, stress was still important to understand in terms of how that individual will be triaged.

Despite IOM's recommendation that SBD measures should be in every electronic health record, the current approach seems to be referring individuals to the proper specialists to address these sensitive issues. Several of the participants included in the study felt that a nurse gauging

an individual's social need and then referring to a social worker on a case-by-case basis was adequate to get the information they needed.

"*We rely a lot on social workers to dig into that more, so a lot of that's captured in their notes….they have a very extensive interview with the patient. That's the part that's time consuming and I think that's why us as case managers, we nurses, we don't wanna dig in to that 'cause it's an hour or two of sitting down with that patient and just pulling out that information. You have to have the appropriate interview skills to be able to know how to capture that information from patients."*

There seemed to be several inconsistencies around whether providers found the data that was available discretely to be reliable or meaningful:

Two nurses, when asked about where they would locate SBD fields discussed the option of looking at differential diagnoses on the problem list, but there was a general disagreement of whether this was a consistent or reliable way to obtain that information.

"I can see how that might be the ideal, but I'm not 100% sure that those problem list items are connected to ICD-9 codes. And then the other problem with the problem lists at least from my perspective, they're not entirely accurate. They're only as good as the physicians who tend to them. And I'm not convinced that to the physicians they're a priority each and every single time they're with a patient. So you've got to take that information with a grain of salt."

A similar discussion came up around face sheets:

Participant 1: The face sheets are always updated.

Participant 2: No, they're not.

Participant 1: Yeah, I guess they could be wrong.

Participant 2: Yeah, they're not always updated.

Another concern that was raised was about discreet fields that auto-populate without the appropriate context.

"*I routinely find things that are in the chart…that I know it was just pulled in automatically from the system, because it doesn't fit the presentation of the patient."*

Accordingly, providers felt they did not look at discreet data points to understand patient's history, but instead would go directly to narratives of the previous encounter.

"*I don't…even think of [discrete fields] as a place to go for information. Because in my mind, it's the equivalent of an electronic Post-It. Not just my Post-It, but everybody's Post-it who's every touched the [EHR], and how reliable is that?...If anything I will rely more on whatever notes are written for the encounter."*

"…I go ahead and I look through the [free-text] notes…you can really get a picture of what actually happened with that patient. And I think that section you have to dictate in…so that's where I go all the time to figure out what's really going on. It gives you a nice picture."

Another concern that was expressed around the reliability of the data was that patients not provide a complete picture of their circumstances. This could be a result of not spending adequate time to get robust information:

"And I think sometimes you get conflicting information, too. And we don't have time. If they are saying this, but their study said this, we can spend a little time figuring them out, but the social workers have the ability to actually dig in and get the truth out, I feel like."

It may also be a matter of patients not being able to answer the question depending on their wherewithal:

Participant 1: The question is…patients are so sick now. Do you think the average patient has the mental capacity to do that?

Participant 2: I think maybe not upon admission…because they really need to process being in the hospital. Maybe after 24 hours.

There were even some concerns that patients would lie or tell partial truths to provides (particularly around sensitive information). This seemed to be of particular concern for vulnerable and homeless populations.

"…80% of that stuff from that [vulnerable] population, when you're talking to them, they're not going to be very accurate in their responses anyway…Right now we ask them just simple things that we need to manage their medical care and it's not accurate. Like 'Where do you get your

medications from' and they're not gonna know…because they were on drugs or they've got a lot of things on their mind. They're out on the street. They carry weapons and things because it's a rough place to stay.

Facilitators to SBD

Theme 1: Alternate methods to capture SBD

Participants were not enthusiastic about adding additional discreet documentation to their workflows. When asked about what alternate approaches they would recommend, many participants mentioned that in an ideal world, they would like to see SBD measures captured by some form of natural language processing.

"I don't think you'd ever wanna see a clinician have to add another discreet field ever…It's just drift into scientific fantasy for a second. A clinician would want to just walk into the patients' room at the bedside, work with the patient, if they could say what they're doing out loud. Have a computer watch what they're doing. Capture all of that. And then let the computer sort it out by itself."

"A headset that's like a real time dictation in to a file maybe. Which probably actually is like you said, not that far off."

"*It would be nice if certain key words were triggered 'social-work' and a social work consult or a social work assessment. That would benefit physicians as well. I think there's probably a disconnect with [free-text] notes. There's a lot of information in an electronic medical records and nobody sees it."*

Some participants discussed tablet options for patients to self-report as a more practical implementation option.

"*We're much closer to getting patients an iPad to fill out the surveys. I think we inundate patients with surveys already and I can imagine there's gonna get to be a point in patient survey fatigue, too."*

"Do you think patients in the in-patient world would have the capacity to answer a question…If we gave them a tablet or some kind of a situation where they could fill out their own, maybe they're more likely to be honest…"

Participants felt that patient self-report options would have the added benefit of potentially eliciting more honest responses from participants.

Theme 2: Closed-Feedback Loops

Participants felt that the barrier of ambiguity around professional responsibility for SBD would be alleviated if there were systems in place to ensure that that the needs were met. One participant mentioned that the best way to alleviate this burden would be to facilitate trusting relationships with the individuals that would be completing follow-up with the patient.

"I'm collecting this data not for…not to check on the box, but trusting that someone follows up. This is valuable to the nurse because of a follow-up…I'm inputting the data so it goes…to the appropriate people, support, and team."

Additionally, while participants did not necessarily want the granular detail behind what follow-up was completed to meet a social need, they wanted basic interoperability to inform them that the referral was completed:

"If a screen somehow was set that it was done or documented, it would help me visualize something easily. We have that for diabetes…when [the educator] has screened, she'll document it as completed and the data gets beamed back to us."

Participant 1: "Do you get a little flag of that information?

Participant 2: "No, that would be nice to have"

Participant 1: "Yeah…have a little green flag, or red flag to see [whether] there have been services within the last 30 days."

Discussion

The overall purpose of this study was to understand provider perspectives on the barriers and facilitators of social and behavioral domains. The sample included in this study included a mix of case managers and nurses from two different facilities, representing several different settings within the hospital (ED, IP, and OR). Despite the participant diversity, the findings from

this study align well with the existing literature on the operational challenges of implementing SBD measures in the EHR.

Collectively, the findings indicate that there are several barriers to implementing the IOM measures as initially proposed, including: 1) not enough time to capture information, 2) concerns about professional responsibility 3) detrimental implications to the patient, and 4) data integrity. However, the groups were receptive to capturing social and behavioral domains, as long as there were considerations made to conveniently integrate it in to their workflow and there were good pathways for closed feedback with partnering organizations.

This has some interesting operational implications when it comes to implementing the IOM's recommendations for standardized SBD domains. For example, it may not make sense to implement SBD measures unless the organizations and frontline staff have adequate community resources for patient referrals. This requires maintenance and continuing education and communication to frontline staff, particularly as government funding priorities shift.

While one of the strengths of the IOM recommendations was detailed metrics and proposed workflows to capture this information, these standards may not make sense for the inpatient population. Participants seemed to think that the appropriate time to capture SBD varied by the acuity of the patient and the type of hospital encounter that was taking place. For example, capturing SBD for patients undergoing elective surgery can occur as a part of a screening process before the patient even arrives for the procedure. An ED encounter on the other hand, is faced with the challenge of a short window of time to engage with a patient who may be acutely ill or traumatically injured, who may not have the capacity to answer possibly complicated and personal questions fully under a stressful situation. Asking questions that seem irrelevant to patients in extreme pain or distress may have implications for trust and quality of care.

Several of the concerns identified by participants are also present in the literature about operationalizing the IOM SBD measures in the EHR, namely: concerns about reliability of the data (theme 4) and professional responsibility (theme 2). A recent article by Garg, Boynton-Jarrett, and Dworkin (2016) provided recommendations to overcome these barriers within the primary care setting, but based on the findings from the focus groups, these recommendations are applicable to acute care settings as well. In the focus groups, participants felt strongly that screening done by a trained professional (e.g., social workers) to elicit honest and comprehensive

responses from the patients. The article by Garg, Boynton-Jarrett, and Dworkin similarly recommends that organizations should avoid risk-stratification models that automatically refer patients to community services. Patient's social needs need to be understood within the context of patients' concerns, priorities, and desire for assistance with material needs.

Another dominant concern seen in this study and Garg, Boynton-Jarrett and Dworkin's work was making sure that after a social need was identified, that the need was met. Screening for any condition in isolation without the capacity to ensure referral and linkage to appropriate treatment is ineffective, and arguably unethical. Despite this, there are relatively few exemplary, evidence-based models that have been about to establish cross-sectional collaboration to meet comprehensive social needs of a patient (eg, housing, food and nutrition, transportation, mental health, human welfare, education, workforce development, and employment). Garg, Boynton-Jarrett and Dworkin (2016) recommend that whenever possible, communities should work to establish a 2-1-1 centralized access strategy or medical home infrastructure to ensure that providers confident in the ability to fulfill the needs that they are identifying.

The two facilitators that were identified by the group: closed-feedback loops between community services and health care providers and alternate methods of capturing SBD. Both of these facilitators merit additional feasibility research. While there is a lot of information about how to get data from a hospital setting out to a community health resource, there is substantially less information about how to get community health services to report back to health care providers that a client has been seen. Getting interoperability of this kind, while desirable, requires the long-term effort of creating an interoperable community health record framework.

Interestingly, natural language processing, one of the proposed solutions to capture SBD, has already been used for SBD domains for several epidemiological studies (Casey et al, 2016). For example, Anderson et al (2015) used natural language processing to extract suicidal ideation from free-text clinical notes. Tobacco and substance use have also been analyzing natural language processing (Chen et al, 2014; Wang et al, 2015). Recently, Vest et al (2017) completed a cross-sectional study to use both structured and unstructured fields to screen for patients in need of one of eight social work services, behavioral health, nutrition counseling, respiratory therapy, financial planning, medical-legal partnership assistance, patient navigation, and pharmacist consultation. The benefit of this approach was that the natural language screening

was only set-up for services that were readily available for patient referral. Creating a standard NLP logic to flag for certain SBD regardless of how they appear in the EHR may provide more opportunity for epidemiological or population health studies without being disruptive to existing provider workflows.

In some ways, the results from this study ran counter to the initial hypothesis. The initial hypothesis for this study was that participants would want to be able to leverage SBD throughout the course of their patient care. However, many of the front-line participants did not want to address the SBD themselves, but rather have the trust, guarantee, or follow-up that someone will ultimately address the need. Providers in the ED seemed to have few concerns about asking the sensitive SBD questions, and felt that most of the areas proposed by the IOM were already included in their workflows (albeit in a non-standard way). Some participants were able to identify scenarios where capturing sensitive SBD data was problematic, including non-critical appointment-based encounters (e.g., Dermatology and Podiatry) or in cases of extremely high-need (e.g., traumatic injuries or cardiac conditions presented in the ED). Future studies may expand on this research by addressing some of the limitations of this study. In particular, while efforts were made to ensure focus groups were homogeneous between leadership and frontline roles, a majority of the differing opinions depended on the setting in which individuals practiced in (e.g., ED, OR, or IP). It would be interesting to either split the groups by clinical setting, or even complete studies solely focused within these niche areas. Another limitation of this study is that it does not address the patient's thoughts or expectations around how and when they would like to be asked this information. Future research should elicit feedback from patients – particularly individuals that the need for additional social resources—about how these SBD measures could be implemented most effectively.

3. STUDY 2

Research Question: Does including physical activity measures in the acute care electronic health record lead to decreased case-mix adjusted length of stay?

Abstract

"Level of physical activity" is a SBD domain that has been nationally prioritized by the Institute of Medicine (IOM). However, the metrics for this domain are currently structured for the outpatient environment. This study examines a naturally occurring experiment at Hawai'i Pacific Health (HPH), where one hospital site implemented physical activity and ambulation measures tailored for the inpatient setting, and other site did not. The intent of this effort was to have clinical staff encourage active movement (rather than excessive bedrest) during hospitalization to improve health outcomes among the acutely ill. A secondary data analysis of EHR data was be conducted to determine whether there is a statistically significant decrease in length of stay for qualified patients. Using a piecewise-regression, and controlling for relevant clinical and demographics, this study did not show a statistically significant difference in CMI-Adjusted ALOS in the case (versus control) site in the post-intervention period. While these findings run counter to the initial hypothesis, the study provides one example of how SBD measures can be integrated in to routine quality improvement efforts in the acute care setting.

Introduction

Inpatient mobilization—defined as an individual's ability to walk, stand, or sit in a chair without assistance during hospitalization—is an essential part of patient care. Best-practice for mobilization, depending on the patient's condition and baseline activity level, is to ambulate patients (i.e., move from one place to another) at least three times per day with incrementally decreasing levels of assistance (Pashikanti & Von, 2012). Despite this, mobilization has been identified in peer-reviewed literature as one of the most frequently missed elements of nursing care (King, 2012). The issue is complicated by the notion that inactivity while in the hospital is a normalized expectation of patients and providers (Cattanach et al, 2014). Studies have found that, while there are recommendations for regular activity during hospitalization, inpatients

spend 75-83% of their wakeful hours lying in bed (Kuys, Dolecka, and Guard, 2011; Brown et al, 2009).

Researching ways to measure and improve inpatient mobility has been a consistent priority among hospitals in developed nations. Consistent mobilization has proven physical, psychological, and social benefits for patients, including fewer post-operative complications, increased levels of patient autonomy, and decreased anxiety and stress among caregivers (Klien et al, 2018; Kalish, Lee, & Dabney, 2014). There are a lot national best practices that encourage mobilization of patients within specific specialty areas. For example, there is a growing evidence around the benefits of mobilizing patients who are on mechanical ventilators, which has led to best practice recommendations for "Early Mobilization in the ICU" (Shehu et al, 2017; Shah et al, 2016; Nydahl,et al, 2017). Another major area of "mobility-related" interventions in the clinical setting is in surgical recovery. This emphasis is in large part due to the "Enhanced Recovery After Surgery" (or ERAS) protocols developed in the 1990s for improved perioperative management of colorectal, vascular and thoracic surgeries wherein "Early Mobilization" is listed as a component of post-operative care (Ljungqvist, Scott, and Fearon, 2017, Melnyk, Casey, Black, and Koupparis, et al, 2011). Even though there are proven benefits of mobilization in these specific areas, there is still debate about which (if any) mobility measures in the inpatient setting are predictive of overarching hospital outcomes (Pavon, Salone, and Hastings, 2017).

This study contributes to the existing literature in several ways. First, it in examines the impact of a nursing-led mobility protocol on a broad inpatient population rather than a specialty-specific area (e.g., ICU or Peri-Operative). Second, it examines a commonly monitored hospital-level metric (Case-Mix Adjusted Average Length of Stay) rather than a mobility-related metric (e.g., whether the patient-specific mobility goal was met). Third, this study includes case and control site, rather than exclusively examining pre- and post-outcomes, as is seen in previous studies (e.g., Hoyer et al, 2016; Yeung, Wessel, Stratford, and Macdermid, 2008)

Mobility as a Social and Behavioral Domain (SBD)

In the previous chapter, examining providers' perspectives on facilitators and barriers to SBD in the EHR, participants mentioned that the IOM measure for physical activity as it is

currently defined is not relevant for the inpatient setting. The IOM measure recommends screening for physical activity by asking the following:

1. On average, how many days per week do you engage in moderate to strenuous exercise (like walking fast, running, jogging, dancing, swimming, biking, or other activities that cause a light or heavy sweat)?
2. On average, how many minutes do you engage in exercise at this level?

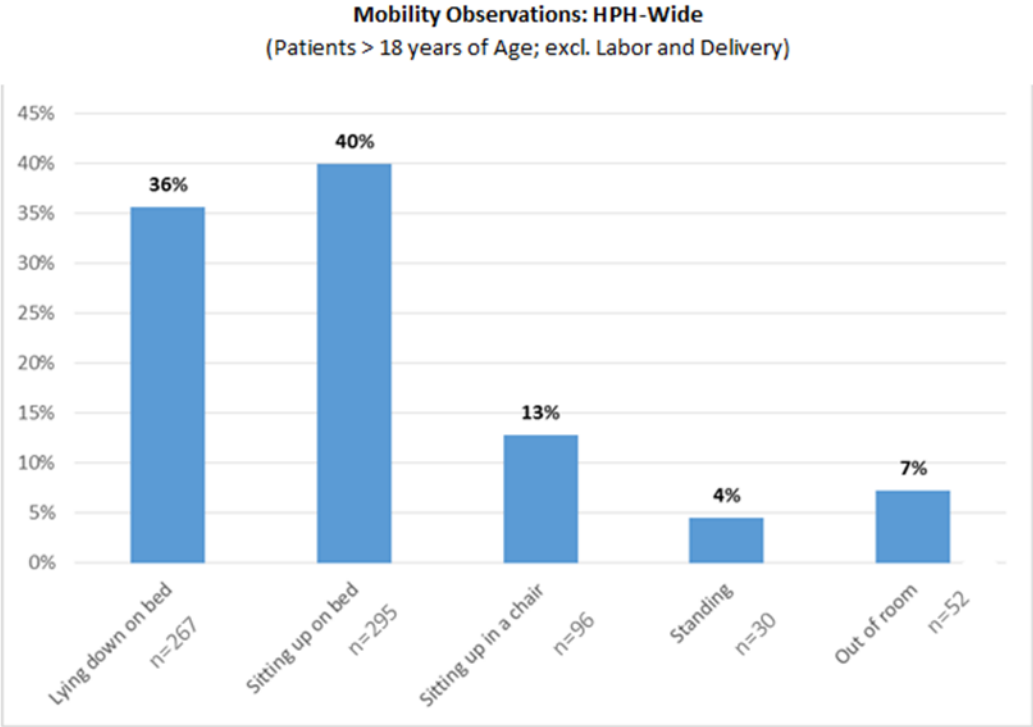
The participant mentioned that at the inpatient setting, nurses are more interested in the individual's "functional status." The nurse wanted to know specifically whether the patient would move independently, whether physical therapists needed to assist, or whether the patient could only participate in activities involving passive range of motion. A different participant, a case manager, mentioned that the "physical activity" measure of interest for them was whether a specific assistive device (e.g., a wheelchair, walker, or cane) was needed to prior to and immediately following the discharge. The case manager cared about these elements for discharge coordination purposes. Specifically, it was the case manager's responsibility to ensure this equipment was available to the patient prior his or her return home from the hospital.

IOM's "physical *activity*" domain was designed to understand whether individuals were participating in healthy behaviors. However, it does not align with how inpatient providers' need to assess overall "physical *ability*." This domain potentially overlooks a vulnerable population within the "Physical Activity Domain"— those who have limited mobility. Mobility (and functional status measures) are often already documented in EHRs, because they could inform patient safety and improve post-discharge care. However, these measures could also have important implications at the public health level, such as informing advocacy for universal design for urban planning within a community. Accordingly, for this study leverages "Mobility," rather than "Physical Activity" as the SBD measure of interest, as it is more reflective of what is currently captured in the inpatient setting.

Mobility Efforts at HPH

This study was the result of a naturally occurring experiment at HPH wherein one facility added standardized mobility measures to the EHR as a routine part of a quality improvement (QI) effort. In July 2015, when HPH examined the baseline levels of inpatient ambulation within each of its four hospitals, to determine whether a formal QI effort was merited. Summer interns

Figure 3.1: Results of the Observational Study of Mobility at HPH, conducted July 29-July 31, 2015

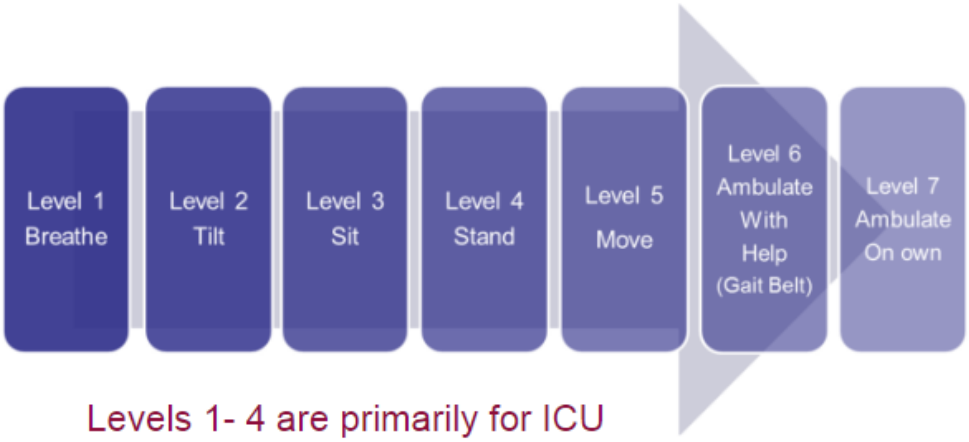


helped conduct an informal survey of patient activity among hospitalized adults (excluding the labor and delivery patients). Over a period of three days, students used a simple tally sheet to document patient activity status during the lunch hour (one observation per room, between the hours of 11am-1pm). This timeframe was selected based on HPH's recommended practice to get patients out of bed during mealtimes. Students recorded whether the patient was lying in bed, sitting in bed, sitting in a chair, standing/walking, or out of the room. Despite having a different sample size and timeframe, our findings at HPH were very similar to the outcomes observed by Kuys, Dolecka and Guard (2011). Patients were lying or sitting in bed for 76% of the 738 encounters observed (see figure 3.1). Following this snapshot survey, we collected data from the internal nursing assessment to determine whether we were capturing baseline physical activity upon admission. However, the data ended up being inaccurate and incomplete. Specifically, the nurses shared that there was a lot of ambiguity and subjectivity involved in the assessment. The question simply asked for patient's mobility level at home, and gave the options of "independent, needs assistance, or total assistance." There was some confusion about what constituted a patient who was able to mobilize independently (*e.g., does it matter if they use a cane? What if they can mobilize independently for short distances but need assistance with the longer distances? etc*).

Sometimes this question would be ignored or skipped if the nurses knew that physical therapy would be involved and completing a more detailed assessment later as a part of the patient's course of care.

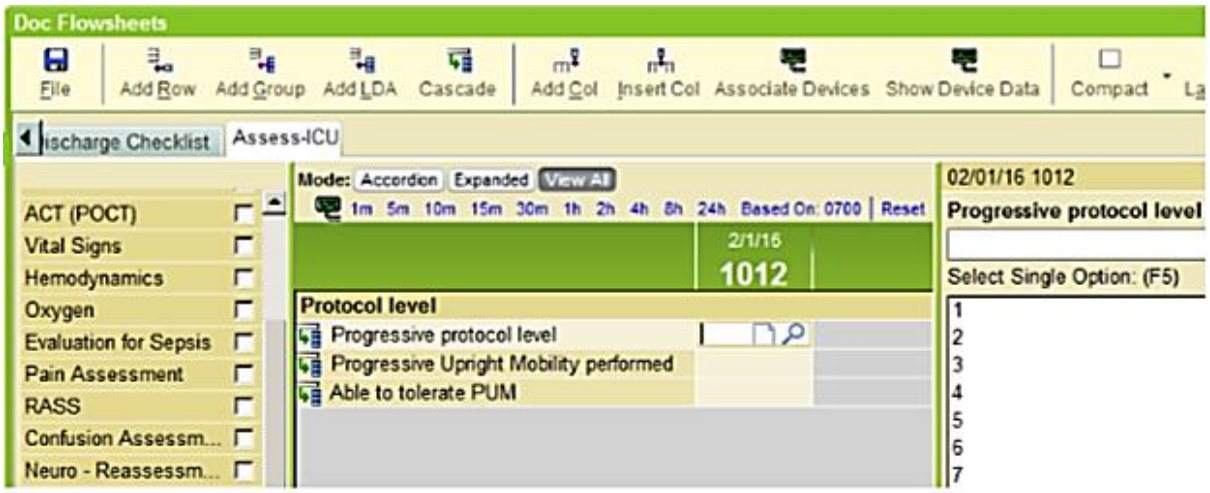
This initial data indicated that additional EHR modifications and staff interventions were needed. In October of 2015, HPH formed a transdisciplinary team to identify methods to improve inpatient mobility on the medical and surgical (non-ICU) hospital units. First, the team completed a more rigorous audit of inpatient activity and discovered that qualified patients were only being mobilized at recommended levels 50-54% of the time. To address this, the team developed a "progressive mobility protocol" that helped frontline staff to 1) identify the initial mobility level of the patient, and 2) clearly delineate the recommended level of physical activity while hospitalized (see figure 3.2).

Figure 3.2: HPH Progressive Upward Mobility Protocol



Additionally, the team developed established places in the EHR to document the patient's initial mobility level upon admission, as well as their progress throughout the hospital stay (shown in figure 3.3, below).

Figure 3.3: Progressive Mobility Protocol Screenshot



These modifications were implemented at one hospital facility on March 1st, 2016. Once these changes were in place, reporting structures became available to help managers determine how often qualified patients are being mobilized. This study compared data from the hospital that completed the EHR modifications against another hospital that maintained existing practices during pre- and post-intervention periods to determine if the effort resulted in a significant decrease in Case Mix Adjusted Average Length of Stay (CMI-Adjusted ALOS). Based on findings in previous literature, it was hypothesized that the "Case" site (where the EHR modifications were completed) would have a more substantial decrease in CMI-Adjusted ALOS in the post-intervention timeframe compared to the "Control" site.

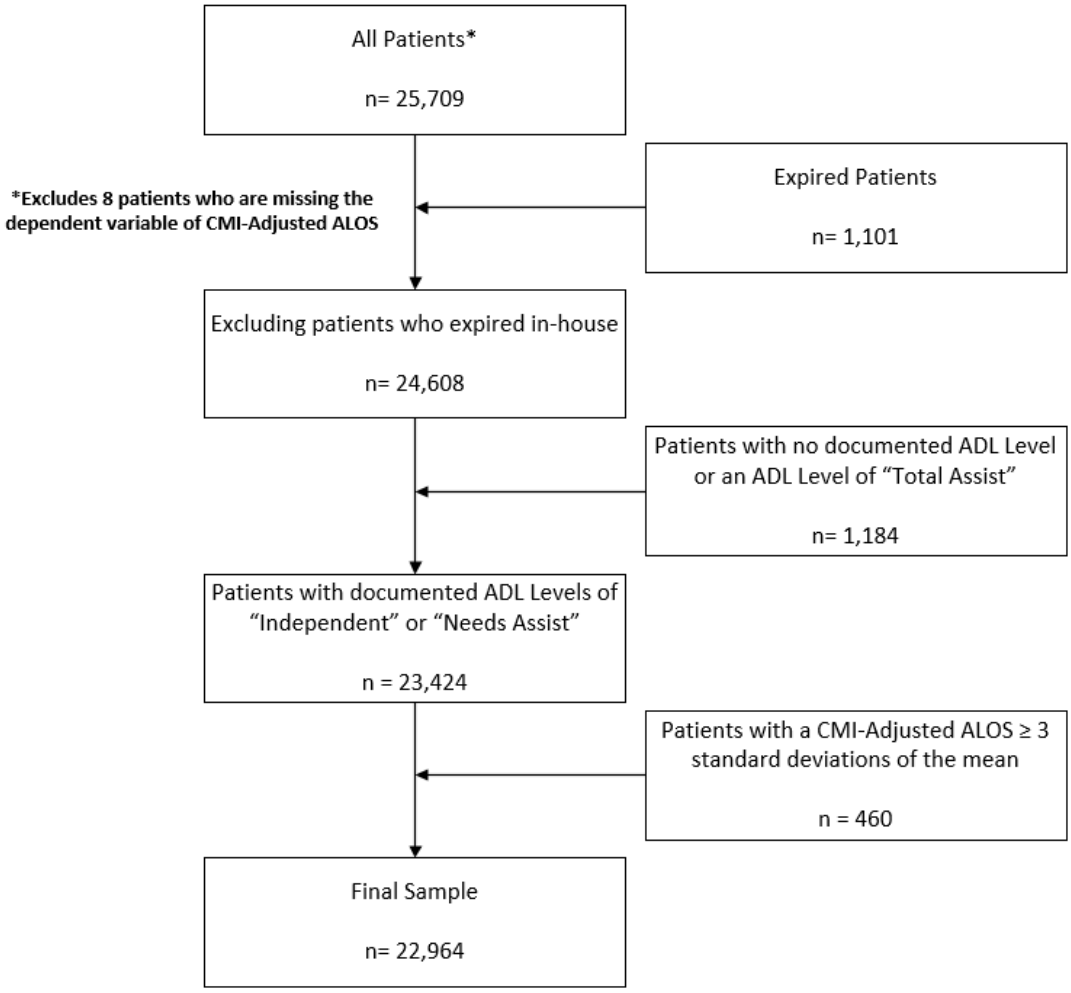
Methods

Data and Inclusion Criteria

IRB approval was obtained from the HPH Research Office via expedited review to complete this study (see appendix 5). A data set of de-identified electronic health record (EHR) data for individuals 18 years or older with hospitalization from May 1, 2015 to April 30, 2017 was collected from two mid-sized urban hospitals in Hawai'i (n=25,717). Records without a documented case-mix adjusted average length of stay (CMI-ALOS) were excluded from the sample (n=8). Any hospitalizations with a discharge disposition of "expired" were excluded from the analysis (n=1,101). Only individuals with activity of daily living levels (ADL levels) of "Independent" or "Needs Assist" were assessed. Individuals with no documented ADL level or an ADL level of "Total Assist" were excluded from the sample (n=1,184). Patients with a CMI-

Adjusted ALOS ≥ 3 standard deviations of the mean were also excluded (n=460). For the final analysis, a total of 22,964 inpatient hospitalizations were used (see figure 3.5).

Figure 3.4: Selection criteria for final sample



Outcome Variable - Case Mix Adjusted Average Length of Stay:

The outcome variable for this study was the widely recognized hospital outcome measure, "Case Mix-Adjusted Average Length of Stay," (CMI-Adjusted ALOS). "Length of Stay" is the duration of time that an individual spends in the hospital (from admission to discharge). The *CMI-Adjusted* ALOS is an acuity-adjusted measure used to normalize hospital length of stay based on the individual's severity of illness. For this study, the CMI-Adjusted ALOS was calculated for every hospitalization after discharge, based on patient's Diagnostic Related Grouper (DRG). Each DRG is assigned an acuity weight (Case-Mix Index; CMI) based

on standards from the Center for Medicare/Medicaid Services. CMI-Adjusted ALOS is a calculated by taking an individual's average length-of-stay (from inpatient admission to discharge) divided by their respective CMI-DRG weight.

Independent Variable – Facility

The first independent variable of interest was "Facility." This was a simple binary variable that flagged whether the patient was hospitalized at the facility where the standardized mobility intervention was completed (i.e., "case" facility) or at the facility where no intervention was performed (i.e., "control" facility or reference site).

Independent Variable – Time

The second independent variable of interest was "Time." Time was coded in several different ways, depending on the phase of analysis. For the descriptive statistics, "Pre/Post Time" was a binary variable that indicated whether the patient's discharge occurred prior to or after the intervention was performed. For the multivariate analysis, "Time" was coded as a continuous variable on a scale of -12 to 12 based on patient's discharge month. -12 to -1 represented the months in the year prior to the intervention and 1 to 12 represented the months in the year after the intervention window. The number 0 served as a breakpoint in time for the piecewise regression. The post-intervention impact also needed to be isolated within the multivariate model. To achieve this, an additional "Post-Time" continuous variable was created where "0" was used for all patient encounters that occurred prior to the intervention window and the "0 to 12" pattern was retained for any patient encounters that occurred during the post-intervention timeframe. This statistical method is also referred to as a piecewise spline (Oosterbaan, 2005).

Control Variables

A total of 33 variables were collected for descriptive statistics. Several demographic factors were collected, including: ethnicity (Caucasian, Chinese, Japanese, Filipino, Hawaiian, Other Pacific Islander, and Other), age group (<65 and ≥65 years old), sex (Male/Female), and insurance (public, private, or other). Several clinical factors were also collected, including admission source (e.g., emergency room, referral, or transfer), length of hospitalization, length of intensive care unit stay, and whether patients had a surgical encounter (Yes/No), whether

patients have a device to assist with mobility (Yes/No), the Elixhauser Comorbidity Index, presence of mental health diagnoses (Yes/No), and discharge disposition (e.g., discharged to home, hospice, skilled nursing facility, etc).

Statistical Analysis - Descriptive

The descriptive statistics were completed in multiple stages. For the first stage of analysis, patients from the case and control hospital sites were summarized by descriptive statistics and compared by type using $\chi 2$ tests or Fisher exact tests (for categorical variables) and Pooled T-Test for continuous variables (if the normality assumption was not satisfied, Satterthwaite T-Test was used). For the second stage of analysis, the hospitalizations were separated by case and control facilities and compared over time. Descriptive statistics of individuals who were hospitalized in year 1 (pre-intervention) and year 2 (post-intervention) were then conducted for each cohort separately to further delineate differences across time. Third and finally, interactions of variables between case and control sites and time (pre- and post-interventional window were tested). To test pre-post differences between case/control sites, general linear modeling was used for continuous outcome variables (i.e. two-way ANOVA) and logistic modeling was used for dichotomous outcome variables. The pre-post differences between sites were estimated by the interaction effects of case/control sites and pre-post time. Two-tailed tests using an α of 0.05 were used to assess the significance for these three analyses; statistically significant factors were included as control variables in the piecewise regression model.

Statistical Analysis – Modeling

As a first step in the analysis, CMI-Adjusted ALOS (aggregated by patients' discharge month) was graphed by facility. Next, piecewise linear regression model was used to create a marginal (or un-adjusted) model. This model estimated the trajectories of ALOS in continuous time with a breakpoint at the time to intervention (no control variables were included). Finally, a piecewise regression model was developed to estimate the CMI-Adjusted ALOS for inpatient hospitalizations, including all of the control variables identified through the descriptive statistics as being statistically significant, as well as the variables of interest, "Facility" (Case/Control) and "Time."

Results

The descriptive statistics were completed for the 22,964 qualitied hospital admissions. Of the 33 descriptive statistics evaluated, only 14 were statistically significant and ultimately included in the summary tables and predictive models. A comparison between case and control facilities (without accounting for pre-post intervention windows) can be found in Table 3.1. This table was to help understand the overarching differences between the facilities. The comparison of variables for exclusively the "case" site (where the intervention occurred) between the pre-post-intervention window (year 1 and year 2) can be found in Table 3.2. This analysis was repeated for the control site, and can be found in Table 3.3. The outcomes across all descriptive statistics, as well as interaction effect (if any) are summarized in Table 3.4.

The first analysis was to compare case and control sites without factoring for time. The case site represented 44.8% (n=10,306) of hospitalizations. The control site represented 55.1% (n=12,658) of hospitalizations. The sites showed statistically significant differences in age demographics, where the case had a higher percentage of individuals who were ≥ 65 years of age ($p<0.01$). Sex also varied by site, with the control site having a higher overall percentage of females ($p<0.05$). When looking at the distribution of race, the case site had a higher percentage of Filipino and Japanese patients (n=2,438 and n=2,936, respectively) compared to the control site, which had a higher overall percentage of Caucasian patients (n=4,169; $p<0.001$). There were also statistically significant differences in how the individuals were admitted to (e.g., emergency, referral, transfers) or discharged from (e.g., Home, Skilled Nursing Facility, other) the hospital ($p=<0.001$ for both variables). Among case and control sites, the case site had a higher percentage of individuals with "public" health insurance (67.0% compared to 61.8%; $p<0.001$).

When looking at variables specifically pertaining to mobility, there were also statistically significant differences between the two hospital facilities. At the case site, 47.6% of hospitalized individuals (n=4,897) were documented as needing a device to assist with mobility during the nurse's admission screening. At the control site, only 37.5% of patients were documented as needing a device to assist with mobility (n=4,739, $p<0.001$). There was also a difference in the percentage of individuals who identified that there had been a change to their ability to complete activities of daily living (ADL) prior to hospitalization. Specifically, a higher percent of patients with a change in ADL were documented at the control site than the case site ($p<0.001$).

There were several other clinical factors that were statistically significant when comparing the two facilities. The case site had a higher percent of individuals with diabetes and dialysis ($p<0.001$). The control site had a higher percent of individuals who had a surgical encounter during their hospitalization and a higher percent of individuals with a sepsis diagnosis ($p<0.001$). There was no statistically significant difference in the percent of individuals who had a mental health diagnosis on their record. The case site had 25.8% (n=2,660) and control site had 26.8% (n=3,388) of individuals with a mental health diagnosis ($p=0.1021$). There was also a statistically significant difference in the Case-Mix Adjusted Average Length of Stay (CMI-Adjusted ALOS) between the two sites, where the case site was directionally higher than the control ($p<0.001$) prior to controlling for any other variables. The case site had an overall higher CMI-Adjusted ALOS (mean [standard deviation], 3.33 [2.27]) compared to the control (3.06 [2.31]).

The next phase of analysis was to consider descriptive variables exclusively by site before and after the intervention. We first consider hospitalization at the case site (n=10,306) that occurred before and after the intervention (n= 5,198 and n=5,108, respectively). This comparison can be found in table 3.2. For this analysis, only three variables showed a statistically significant change over time: admission source, mental health diagnoses, and change in ADL. For admissions at the case site, there was an increase in the percent of emergency admissions and a decrease in referrals when comparing year one and year two ($p<0.001$). There was also a statistically significant difference in the percent of individuals with a documented mental health diagnosis. Individuals with a mental health diagnosis documented on their record almost doubled year over year, increasing from 18.9% (n=982) to 32.9% (n=1,678; $p<0.001$). There was also a slight, significant increase in individuals with a documented change in ADL level over time at the case site, moving from 30.9% to 3.332% year over year ($p<0.01$). The other demographic variables (e.g., age, sex, race, insurance) which were statistically significant between case and control sites were not statistically significant for the case site by time. Similarly, the remaining clinical variables (e.g., number of individuals with diabetes, dialysis, or a sepsis diagnosis) showed no significant changes between year one and year two.

The results over time were very similar for the control site (n=12,658; comparison found in table 3.2). For the control site, 6,202 (49%) of hospitalizations occurred in year one and 6,456 occurred in year two. Only two variables showed a statistically significant change over time: age

upon admission (<65 and ≥65) and mental health diagnoses. In year two, the percent of individuals ≥ 65 increased from 51.1% to 53.3% ($p<0.001$). As with the case site, there was a statistically significant difference in the percent of individuals with a documented mental health diagnosis. Individuals with a mental health diagnosis increased from 19.5% (n=1,209) to 33.8% (n=2,179; $p<0.001$). No other tested variables had a statistically significant difference between year one and year two at the control site.

For the final part of description statistics, interactions were tested for the variables among four categories: 1) Case | Pre-Intervention, 2) Case | Post Intervention, 3) Control | Pre-Intervention, and 4) Control | Post Intervention. For this analysis, only admission source showed statistically significant differences across all four categories ($p<0.001$). Table 3.4 summarizes the p-values across all of the analyses (asterisks are used to denote the α – level of significance).

Table 3.1: Descriptive statistics for hospital sites with and without standardized documentation for mobility (N=22,964)

	Case (n=10,306)	Control (n=12,658)	P-Value
Age Group			<0.01
<65	4,713 (45.7%)	6,036 (47.7%)	
≥65	5,593 (54.3%)	6,622 (52.3%)	
Sex			<0.05
Male	5,361 (52.0%)	6,767 (53.5%)	
Female	4,945 (48.0%)	5,891 (46.5%)	
Race			<0.001
Caucasian	1,575 (15.3%)	4,169 (32.9%)	
Chinese	324 (3.1%)	724 (5.7%)	
Filipino	2,438 (23.7%)	1,352 (10.7%)	
Hawaiian	1,647 (16.0%)	1,502 (11.9%)	
Japanese	2,936 (28.5%)	2,817 (22.3%)	
OPI	729 (7.1%)	813 (6.4%)	
Other	657 (6.4%)	1,281 (10.1%)	
Admission Source			<0.001
Emergency	8,639 (83.8%)	8,341 (65.9%)	
Referral	1,427 (13.9%)	2,856 (22.6%)	
Transfers	238 (2.3%)	1,447 (11.4%)	
Device			<0.001
Yes	4,897 (47.6%)	4,739 (37.5%)	
No	5,387 (52.4%)	7913 (62.5%)	
Change in ADL			<0.001
Yes	3,296 (32.1%)	3,747 (29.6%)	
No	6,993 (68.0%)	8,902 (70.4%)	
Diabetes			<0.001
Yes	4,311 (41.8%)	3,910 (30.9%)	
No	5,995 (58.2%)	8,748 (69.1%)	

Dialysis			<0.001
Yes	963 (9.3%)	559 (4.4%)	
No	9,343 (90.7%)	12,099 (95.6%)	
Surgery			<0.001
Yes	3,309 (32.1%)	4,797 (37.9%)	
No	6,997 (67.9%)	7,861 (62.1%)	
Sepsis			<0.001
Yes	1,556 (15.1%)	2,657 (21.0%)	
No	8,750 (84.9%)	10,001 (79.0%)	
Insurance			<0.001
Private	3,331 (32.3%)	4,647 (36.7%)	
Public	6,904 (67.0%)	7,816 (61.8%)	
Other	71 (0.7%)	195 (1.5%)	
Discharge Disposition			<0.001
Home	6,846 (66.4%)	9,740 (77.9%)	
Skilled Nursing Facility	1,181 (11.5%)	1,204 (9.5%)	
Other	2,279 (22.1%)	1,714 (13.5%)	
Mental Health Diagnosis			0.1021
Yes	2,660 (25.8%)	3,388 (26.8%)	
No	7,646 (74.2%)	9,270 (73.2%)	
CMI-Adjusted ALOS	3.33 (2.27)	3.06 (2.31)	<0.001

Table 3.2: Descriptive statistics for year one and year two at the "case" site (before and after adding standardized mobility fields; N=10,306).

	Pre-Intervention (n = 5,198)	Post-Intervention (n= 5,108)	P-Value
Age Group			0.5819
<65	2,391 (46.0%)	2,322 (45.5%)	
≥65	2,807 (54.0%)	2,786 (54.5%)	
Sex			0.1349
Male	2,666 (53.1%)	2,695 (52.8%)	
Female	2,352 (46.9%)	2,413 (47.2%)	
Race			0.7248
Caucasian	777 (15.0%)	798 (15.6%)	
Chinese	159 (3.1%)	165 (3.2%)	
Filipino	1,212 (23.3%)	1,226 (24.0%)	
Hawaiian	829 (16.0%)	818 (16.0%)	
Japanese	1,514 (29.3%)	1,422 (27.8%)	
OPI	378 (7.3%)	351 (6.9%)	
Other	329 (6.3%)	328 (6.4%)	
Admission Source			<0.001
Emergency	4,295 (82.6%)	4,344 (85.0%)	
Referral	800 (15.4%)	627 (12.3%)	
Transfers	101 (1.9%)	137 (2.7%)	
Device			0.7230
Yes	2,460 (47.4%)	2,437 (47.8%)	
No	2,725 (52.6%)	2,662 (52.2%)	

Change in ADL			<0.01
Yes	1,603 (30.9%)	1,693 (33.2%)	
No	3,592 (69.1%)	3,401 (66.8%)	
Diabetes			0.6226
Yes	2,162 (41.6%)	2,149 (42.1%)	
No	3,036 (58.4%)	2,959 (57.9%)	
Dialysis			0.2055
Yes	467 (9.0%)	496 (9.7%)	
No	4,731 (91.0%)	4,612 (90.3%)	
Surgery			0.3521
Yes	1,691 (32.5%)	1,618 (31.7%)	
No	3,507 (67.5%)	3,490 (68.3%)	
Sepsis			0.6284
Yes	776 (14.9%)	780 (15.3%)	
No	4,422 (85.1%)	4,328 (84.7%)	
Insurance			0.7173
Private	1,686 (32.4%)	1,645 (32.2%)	
Public	3,473 (66.8%)	3,431 (67.2%)	
Other	39 (0.8%)	32 (0.6%)	
Discharge Disposition			<0.01
Home	3,523 (67.8%)	3,323 (65.1%)	
Skilled Nursing Facility	544 (10.5%)	637 (12.5%)	
Other	1,131 (21.8%)	1,148 (22.5%)	
Mental Health Diagnosis			<0.001
Yes	982 (18.9%)	1,678 (32.9%)	
No	4,216 (81.1%)	3,430 (67.2%)	
CMI-Adjusted ALOS	3.45 (2.35)	3.20 (2.17)	1.000

Table 3.3: Descriptive statistics for year one and year two at the “control” site (where no intervention was performed; N=12,658)

	Pre-Intervention (n=6,202)	Post-Intervention (n=6,456)	P-Value
Age Group			<0.001
<65	3,031 (48.9%)	3,005 (46.6%)	
≥65	3,171 (51.1%)	3,451 (53.5%)	
Sex			0.7321
Male	3,306 (53.3%)	3,461 (53.6%)	
Female	2,896 (46.7%)	2,995 (46.4%)	
Race			0.8915
Caucasian	2,048 (33.0%)	2,121 (32.9%)	
Chinese	361 (5.8%)	363 (5.6%)	
Filipino	677 (10.9%)	675 (10.5%)	
Hawai‘ian	721 (11.6%)	781 (12.1%)	
Japanese	1,386 (22.4%)	1,431 (22.2%)	
OPI	397 (6.4%)	416 (6.4%)	
Other	612 (9.9%)	669 (10.4%)	
Admission Source			0.4147

Emergency	4,128 (66.6%)	4,213 (65.3%)	
Referral	1,372 (22.1%)	1,484 (23.0%)	
Transfers	694 (11.2%)	753 (11.7%)	
Device			0.2407
Yes	2,290 (36.9%)	2,449 (38.0%)	
No	3,909 (63.1%)	4,004 (62.1%)	
Change in ADL			0.7425
Yes	1,827 (29.5%)	1,920 (29.8%)	
No	4,369 (70.5%)	4,533 (70.3%)	
Diabetes			0.3213
Yes	1,890 (30.5%)	2,020 (31.3%)	
No	4,312 (69.5%)	4,436 (68.7%)	
Dialysis			0.8700
Yes	272 (4.4%)	287 (4.5%)	
No	5,930 (95.6%)	6,169 (95.6%)	
Surgery			0.9599
Yes	2,349 (37.9%)	2,448 (37.9%)	
No	3,853 (62.1%)	4,008 (62.1%)	
Sepsis			0.0957
Yes	1,340 (21.6%)	1,317 (20.4%)	
No	4,862 (78.4%)	5,139 (79.6%)	
Insurance			0.0576
Private	2,264 (36.5%)	2,383 (36.9%)	
Public	3,826 (61.7%)	3,990 (61.8%)	
Other	112 (1.8%)	83 (1.3%)	
Discharge Disposition			0.8006
Home	4,780 (77.1%)	4,960 (76.8%)	
Skilled Nursing Facility	579 (9.3%)	625 (9.7%)	
Other	843 (13.6%)	871 (13.5%)	
Mental Health Diagnosis			<0.001
Yes	1,209 (19.5%)	2,179 (33.8%)	
No	4,993 (80.5%)	4,277 (66.3%)	
CMI-Adjusted ALOS	3.16 (2.36)	2.96 (2.27)	1.000

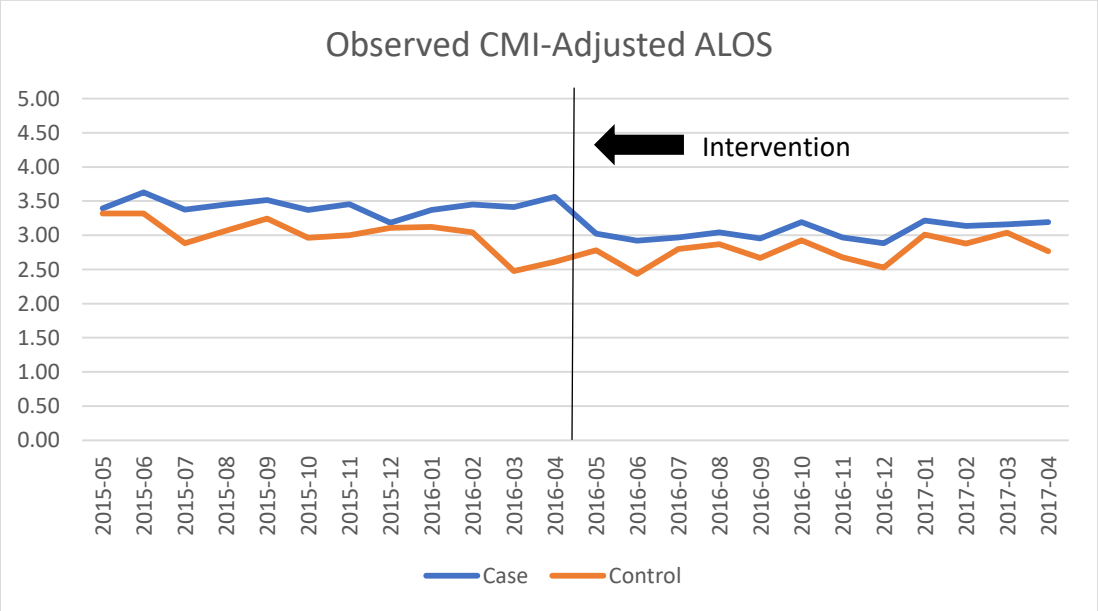
Table 3.4: Descriptive Statistics and Interactions between Case Site, Control Site, and Time for sites with and without standard mobility documentation

	Site Difference	**Case Over Time**	**Control Over Time**	**Interaction (Symbol)**	**Interaction (Actual)**
Age Group	**	-	***	-	0.1779
Sex	*	-	-	-	0.3781
Race	***	-	-	-	0.1349
Admission Source	***	***	-	***	<0.001
Device	***	-	-	-	0.5894
Change in ADL	***	**	-	-	0.0933
Diabetes	***	-	-	-	0.7387
Dialysis	***	-	-	-	0.5150
Surgery	***	-	-	-	0.4621

Sepsis	***	-	-	-	0.1573
Insurance	***	-	-	-	0.9351
Discharge Disposition	***	**	-	-	0.0535
Mental Health Diagnosis	-	***	***	-	0.9774
CMI-Adjusted ALOS	***	-	-	-	0.3147

For the multi-variate analysis, statistically significant variables and interactions were used to complete a piece-wise regression with a breakpoint for time, where CMI-Adjusted ALOS was the outcome measure. In order to achieve the piece-wise regression, the independent variable of "Time" for the 2-year sampling frame was coded on a scale of -12 to 12. The variable of "Time" assigned based on the patient's month of discharge, where -12 to -1 was year 1, zero was the point of intervention, and 1 to 12 was year 2. Before beginning multi-variate analyses, the observed CMI-Adjusted ALOS for each hospital (averaged by patient discharge month) was graphed (Figure 3.5).

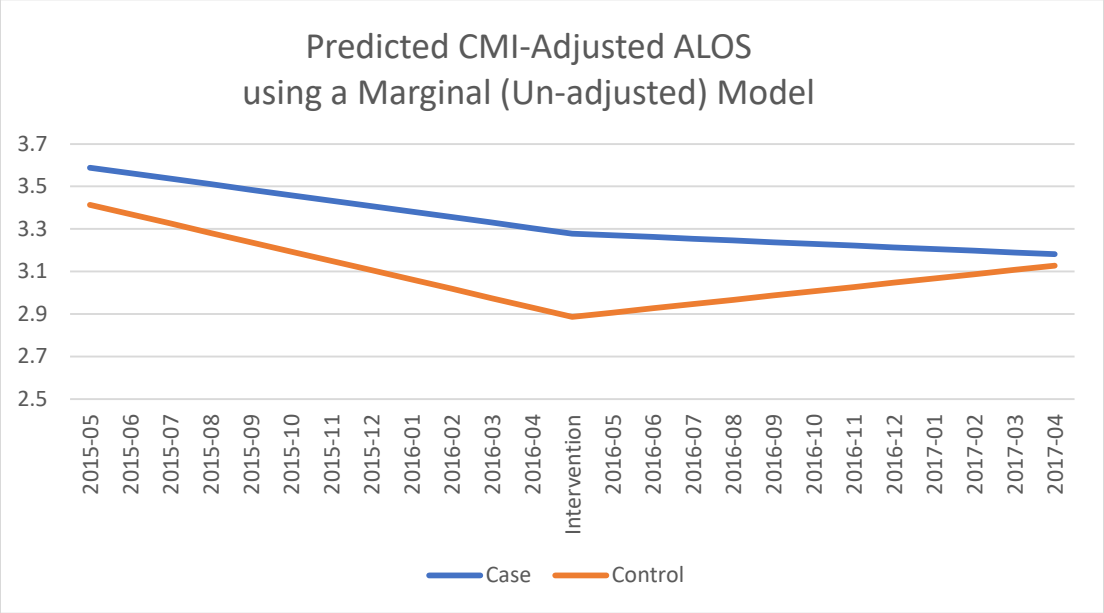
Figure 3.5: Observed CMI-Adjusted ALOS for Case and Control Facilities



As a first step to examine this model, a marginal (or un-adjusted) slope was created using only the variables of "Time" and "Facility" to determine slope for CMI-Adjusted ALOS without adjusting for other factors. For the marginal model, the predicted slope for CMI-Adjusted ALOS during the pre-intervention for the case and control sites were -0.03 and -0.04,

respectively. The post-intervention slopes for case and control sites were -0.01 and +0.02, respectively (see figure 3.6).

Figure 3.6: Marginal (Unadjusted) Model of CMI-Adjusted ALOS for Case and Control Sites



After this analysis was completed, additional control variables identified through descriptive statistics were added to the model. The overall model had a p-value <0.001. The R-Squared value was 0.1420. All variables, with the exception of sex (male/female) retained statistical significance within the model. P-values for each variable from the multivariable analysis are listed in Table 3.5. For the adjusted model, the predicted slope for CMI-Adjusted ALOS during the pre-intervention time-frame for the case and control sites were -0.03 and -0.02, respectively. The post-intervention predicted slope for CMI-Adjusted ALOS was -0.05 and -0.09, respectively (see Figure 3.7).

Figure 3.7: Predictive Model of CMI-Adjusted ALOS for Case and Control Sites after Including Control Variables

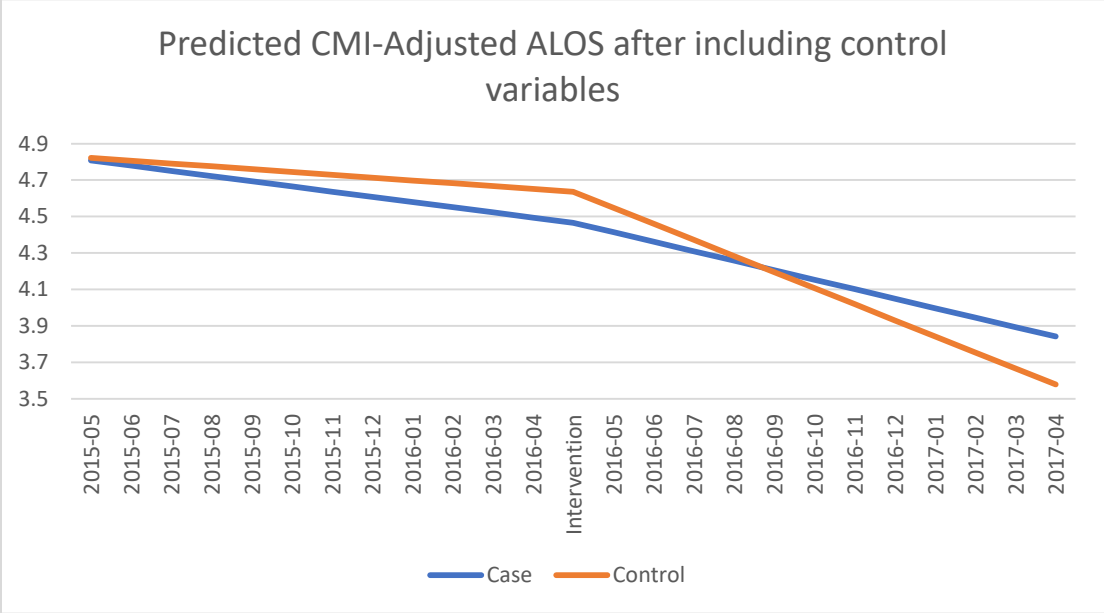


Table 3.5: Marginal model predicting CMI-adjusted average length of stay for two hospital facilities on O‘ahu (N=22,964).

	Parameter Estimate	**Standard Error**	**P-Value**
Intercept	2.89	0.04	<0.0001
Entity (Case/Control)	0.39	0.06	<0.0001
Time (Continuous| -12, 12)	-0.04	0.01	<0.0001
Time (Post, Continuous | 0,12)	0.06	0.01	<0.0001
Entity/Time Interaction	0.02	0.01	0.0406
Entity/Post-Time Interaction	-0.05	0.02	0.0085

Table 3.6: Multivariate model predicting CMI-adjusted average length of stay for two hospital facilities on O‘ahu (N=22,964).

	Parameter Estimate	**Standard Error**	**P-Value**
Intercept	4.64	0.19	<0.0001
Entity (Case/Control)	-0.17	0.05	0.0018
Time (Continuous| -12, 12)	-0.02	0.02	0.4789
Time (Post, Continuous | 0,12)	-0.07	0.04	0.0877
Entity/Time Interaction	-0.01	0.01	0.1160
Entity/Post-Time Interaction	0.05	0.02	0.0027
Pre/Post/Admission Source Interaction			

Referral	0.01	0.09	0.8945
Transfer	0.19	0.12	0.1092
Emergency Room	0.07	0.06	0.3027
Age Group (>65)	-0.26	0.03	<0.0001
Sex (Female)	-0.03	0.03	0.3404
Race			
Chinese	-0.14	0.07	0.0464
Filipino	-0.11	0.05	0.0173
Hawaiian	0.01	0.05	0.8384
Japanese	-0.22	0.04	<0.0001
Other Pacific Islander	0.02	0.06	0.7543
Caucasian	Ref		
Admission Source			
Referral	-1.08	0.06	<0.0001
Transfer	-0.44	0.08	<0.0001
Emergency Room	Ref		
Device	0.35	0.03	<0.0001
Change in ADL	0.16	0.03	<0.0001
Diabetes (Yes)	0.10	0.03	0.0016
Dialysis	-0.15	0.06	0.0086
Surgery (Yes)	-0.49	0.03	<0.0001
Sepsis	0.32	0.04	<0.0001
Insurance			***
Public	0.08	0.03	0.0151
Other	-0.11	0.13	0.4249
Private	Ref		
Discharge Disposition			
Skilled Nursing Facility (SNF)	1.31	0.05	<0.0001
Other	0.57	0.04	<0.0001
Home	Ref		
Mental Health Diagnosis (Yes)	0.18	0.03	<0.0001

Discussion

For this study, one hospital facility implemented a nurse-driven inpatient mobility protocol that collected patients' baseline mobility level, frequency of ambulation, and progression of mobility throughout the hospital stay. Increased inpatient mobilization has been shown to improve a variety of patient outcomes, including decreased pressure ulcers and decreased instances of hospital acquired respiratory infection. For this hospital facility however, the measures are used very pragmatically to: 1) document that mobility actually took place while the patient was on the unit, and 2) inform patients and families of the expected activity frequency and level post-discharge. These measures have been studied for specific hospital areas (e.g., peri-operative, ICU) and specific populations (e.g., geriatric, cardiac, or neurology patients), but there are fewer studies available that assess the impact of mobility on broad inpatient populations (Pavon, Salone, and Hastings, 2017). This study contributes to the current literature by examining an overarching outcome measure (CMI-Adjusted ALOS) for a broad inpatient population rather than an intervention/population-specific outcome measure (e.g., increased frequency of mobilization, improved functional status, etc).

A retrospective analysis of EHR records from both a "case" (with the intervention) and "control" sites was completed. The hypothesis for this study was that the "case" site would have a more significant decrease in CMI-Adjusted ALOS than the "control" site after accounting for relevant control variables. A multivariate model was used to examine trends in CMI-Adjusted ALOS among the two sites. In the marginal (unadjusted) model which mapped CMI-Adjusted ALOS against the variables of "Time" and "Facility" (Case/Control), the hypothesis appeared to be correct, where the CMI-Adjusted ALOS for the case site was decreasing by a rate of -0.01 and the control site's CMI-Adjusted ALOS was increasing by +0.02. However, after controlling for a number of factors that varied across sites and within sites over time, the CMI-Adjusted ALOS no longer followed the hypothesized trends. After controlling for relevant factors, the case site CMI-Adjusted ALOS decreased by -0.05 and the control site decreased by -0.09.

Limitations:

A major limitation to this study was that LOS is difficult to attribute exclusively to inpatient mobility efforts, because there are several concurrent quality improvement efforts in place to impact this measure. This limitation often exists in hospital operations research. Examining two data from two different sites, with one with and one without intervention, was

one method to isolate the impact of these EHR modifications. Similarly, the ways in which the patient population changed over time could have an impact on the post-intervention results. The descriptive statistics showed that year-over-year, HPH saw a higher percentage of emergency admissions. There was also a higher percent of patients year-over-year who were hospitalized for a condition that in some way hampered their ability to complete Activities of Daily Living (or ADL). It is possible that there are other shifts in the patient population that could impact the effectiveness of the mobility-based intervention that were not included in this study.

Additional information on each facility's CMI-Adjusted ALOS score compared to national benchmarks may be useful to consider study findings. It is worth noting that in year two of this study, the control site was 0.01 above of the Center for Medicare and Medicaid's Service's expected CMI-Adjusted ALOS for its population (the control site was 0.04 above the expected CMI-Adjusted ALOS). One potential explanation for the minimal (or non-existent) change in the CMI-Adjusted ALOS at the control site during the post-interventional timeframe was that there simply was not a safe operational threshold to decrease CMI-Adjusted ALOS much further, regardless of what benefits the mobility efforts may or may not have provided.

Finally, the last factor that is difficult to account for is whether the "Control" facility was completing nursing-led mobility efforts with the patients, just without documenting those activities in the electronic health record. It is possible, since both hospitals belong to the same parent organization, that the practices were adopted at the "Control" site, without a formal QI effort involved.

Conclusions and Future Research Implications:

While mobility-based interventions have decreased length of stay for specific populations, the multivariate model for this study did not show a decrease in CMI-Adjusted ALOS for the broad inpatient population the post-intervention timeframe a site where a mobility-based intervention was performed (compared to a control facility where no intervention was completed). Further research is needed to determine whether mobility measures can be used as a predictor of overarching hospital outcomes. An area for future study may be measuring nursing led-mobility protocols against patient and family satisfaction measures. Frequent mobility during a hospitalization has been shown in other studies to make patients and families feel more adequately prepared for discharge. Accordingly, patient and family satisfaction may be a better

measure of success for nurse-led mobility protocols, particularly for hospitals that are already at or below their facilities' expected CMI-Adjusted ALOS.

Additionally, this study illustrates that SBD measures can be added to the EHR as a part of routine quality improvement processes, as long as the outcome is nested within the context of improved patient care. In the previous chapter (i.e., Study 1), providers expressed reluctance toward adding SBD measures discretely to the EHR. However, because "Mobility" was presented as a part of a quality improvement effort, it was adopted with relative ease. Additional thought should be given to how the remaining 11 recommended IOM SBD domains could be woven in to quality improvement projects in acute care settings. For example, SBD measures can be included in efforts to reduce readmissions, assist with discharge improvement, or improving patient health by facilitating referrals to appropriate community resources. Implementing SBD measures iteratively via quality improvement processes (such as the one included in this study) may serve as less disruptive way to integrate SBD data capture in the acute care electronic medical record.

4. STUDY 3

Abstract

The impact of social factors on health care outcomes is widely recognized. Health systems are encouraged to add social and behavioral measures to electronic health records (EHR), but limited research demonstrates how to leverage this information. We assessed two social factors collected from the EHR - social isolation and homelessness - in predicting 30-day potentially preventable readmissions (PPR). EHR data was collected from May 2015 to April 2017 from inpatients at two metropolitan hospitals on O‘ahu, Hawai‘i (after exclusions: N=21,274). We performed multivariable logistic regression models predicting 30-day PPR by “living alone” (vs. “living with others”) and “documented homelessness” (vs. no documented homelessness), controlling for relevant factors, including age group, race/ethnicity, gender, and comorbidity. Among the 21,274 index hospitalizations, 16.50% (3,505) were individuals living alone and 11.21% (2,385) were homeless; 4.38% (971) hospitalizations had a 30-day PPR. PPR did not differ significantly in descriptive statistics by living alone (3.6%; 127) vs. not (4.3; 772; p=0.09) but did by homelessness (5.3%; 126) vs not (4.1%; 771; p=0.01). In multivariable models, neither living alone nor homelessness were significantly associated with PPR. Factors that were significantly associated with a PPR included comorbidity, discharge settings, and use of assistive device. Homelessness predicted PPR in descriptive analyses. Neither predicted PPR once other factors were controlled. Instead, indicators of physical frailty and increasing illness were significant. Findings from this study demonstrate the importance of research for refining, collecting, and applying social factor data obtained through acute care EHRs.

Introduction

Based on widespread recognition of the importance of social factors to health care outcomes, the Institutes of Medicine (IOM) provided recommendations for social and behavioral domain (SBD) measures to be documented in the electronic health record (EHR). Many health systems now collect some data around social factors, but practical and logistical questions remain, including how to feasibly, systematically collect such data within routine clinical care and how to use this data for more effective population health management (Hripcsak, Forrest, Brennan and Stead, 2015; Holt-Lunstad, Robles, Sbarra, 2017; Shortell, Washington, Baxter, 2009)

"Social Connection and Isolation" was one domain recommended by the IOM (IOM, 2014). A lack of social relationships has been associated with a number of health outcomes, including morbidity, mortality, and functional decline (Pantell et al, 2013; Leigh-Hunt et al, 2017; Friedler, Crapser, McCullough, 2015). There are two substantial gaps in the literature. First, there is limited research on whether social isolation plays a role in overall healthcare utilization (Greysen et al, 2017; Valtorta, Moore, Barron, Stow, and Hanratty, 2018). Second, the measure of "social isolation" is typically collected outside of the EHR, via self-reported survey or interview (Pantell et al, 2013; Rico-Uribe et al, 2018; Stopford, Winkly, and Ismail, 2013; Pimouguet et al, 2015). It is thus rarely found in analyses of administrative inpatient data.

Another critical social factor potentially contributing to inpatient health care utilization and readmission is homeless. Homelessness is also not routinely collected by health care systems in the EHR and has been associated with readmissions, as well as overall morbidity and early mortality, in several recent studies (Saab, Nisenbaum, Dhalla, and Hwang, 2016; Doran et al, 2013).

The study objective was to take advantage of "social isolation" and homeless variables as captured in a health system's EHR for over two years. We specifically examine if these variables have predictive value for 30-day potentially-preventable readmission (PPR), a key measure of health care quality (van Walraven, Jennings, and Forster, 2012). We hypothesize that individuals who are documented as "Living Alone" and "Homeless" will have a higher PPR compared to those without these designations.

Methods

Data and Inclusion Criteria:

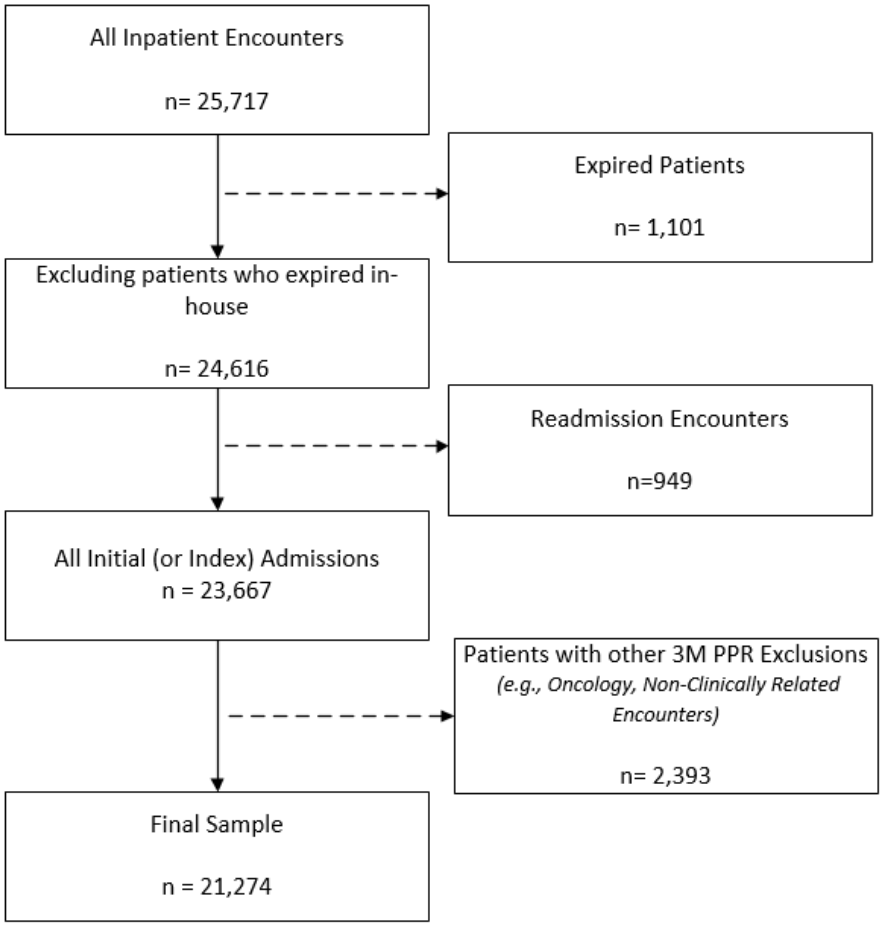
Electronic health record (EHR) data for individuals 18 years or older with at least one inpatient hospitalization from May 1, 2015 to April 30, 2017 was collected from two mid-sized urban hospitals on Oahu, Hawai‘i (n=25,717; IRB approval: 45 CFR 46). Any hospitalizations that resulted in death (i.e., discharge disposition of “expired”) were excluded from the analysis (n=1,101). This data uniquely identified individuals longitudinally. Using this unique identifier, each individual’s first inpatient hospitalization within the study period was identified. These initial hospitalizations were flagged to indicate whether they resulted in a 30-day PPR (Yes/No) using the 3M PPR methodology (Goldfield et al, 2008). The 3M PPR methodology has been extensively used and validated (methodology described in more detail in subsequent paragraphs; 3M PPR, 2018). Individuals’ subsequent readmission encounters were excluded from the sample (n=949) to prevent high-utilization individuals from biasing our understanding of demographic and clinical factors predicting PPR in general.

Hospitalizations that were not considered eligible under the 3M PPR methodology were also excluded (n=2,393). This included, for instance, readmissions that are not clinically-related (e.g., a hospital admission for pneumonia followed by a hospitalization for an appendectomy), an admission with multiple traumas (where multiple hospitalizations may be medically necessary), and individuals who are currently in chemotherapy treatment and likely to return to the hospital (3M PPR, 2018). For the final analysis, a total of 21,274 inpatient hospitalizations were used (see figure 1). SAS Version 9.4 was used to complete both descriptive statistics and multivariable modeling.

Outcome Variable – 30-day PPR

Our outcome was a binary variable that indicated whether an individual’s initial hospitalization during the study timeframe resulted in a 30-day potentially preventable readmission (y/n) according to the 3-M PPR methods (Matthews, Alder, Forrest and Stead, 2016; Sentell, Ahn, Taira, and Miyamura, et al, 2016).

Figure 4.1: Selection Criteria for Study 3



Independent Variable—Lives Alone

At both hospitals included in the study, the "lives alone" has been collected consistently since October 2015. Specifically, nurses ask patients to identify "who they live with" as a part of the admission process. Case managers are required to populate this field if it is missed during the admission process. Nurses and case managers are allowed to select one or more of the following options: alone, caregiver, family, parent, partner, roommate, spouse, or other. The information from this field was used to categorize patients in to two groups, either as individuals who "live alone" or individuals who "live with others."

Independent Variable—Homelessness

For this variable, the reporting team created a wild card search for "*homeless*" in a number of our free-text fields for "residence" and collated them as a 0/1 flag. The information

from this field was used to categorize patients in to two groups, either as individuals with "documented homelessness" or not.

Control Variables

Several demographic factors were considered, including: ethnicity (Caucasian, Chinese, Japanese, Filipino, Native Hawaiian, Other Pacific Islander, and Other), age group (<65 and ≥65 years old), sex (Male/Female), and insurance (public, private, or other). Several clinical factors were also collected, including admission source (e.g., emergency room, referral, or transfer), length of hospitalization, length of intensive care unit stay, whether patients had a surgical encounter (Yes/No), whether patients have a device to assist with mobility (Yes/No), the Elixhauser Comorbidity Index, presence of mental health diagnoses (Yes/No), and discharge disposition (e.g., discharged to home, hospice, skilled nursing facility, etc.). Data for all independent and control variables were taken from the index admission.

Statistical Analysis – Descriptive Statistics

For the first stage of analysis, patients with and without 30-day PPR were summarized by descriptive statistics using $\chi 2$ tests or Fisher exact tests (for categorical variables) and two-sample t-tests for continuous variables. Two-tailed tests using an α of 0.05 were used to assess the significance for these analyses in predicting 30-day PPR; statistically significant factors were included as control variables in the logistic regression equations.

Additional Analyses

Stratified analyses were also completed as a part of this study. However, these analyses did not substantially alter the multi-variable analysis. Supporting tables can be found in Appendix 6.

Statistical Analysis – Modeling

For the second stage of analysis, a logistic regression model was developed to estimate the likelihood of PPR after the index hospital admission, using control variables identified through the descriptive statistics as being statistically significant ($p<0.05$), as well as the two independent variables of interest "lives alone" (Yes/No) and homeless (Yes/No).

Results

Among the 21,274 index hospitalizations, 16.5% (3,505) were individuals living alone and 11.21% (2,385) were homeless. Of the index hospitalizations, 4.38% (971) hospitalizations had a 30-day PPR. This did not differ significantly in descriptive statistics by living alone (3.6%; 127) vs. not (4.3%; 772; p=0.05). Those who were homeless (5.3%; 126) were significantly more likely to have a PPR than those who were not homeless (4.1%; 771; p=0.006) in the descriptive analyses.

More demographic and clinical information for the 21,274 qualified hospital admissions are shown in Table 1 by 30-day PPR (Yes/No). No significant differences in age, either as a continuous or categorical variable (<65 or ≥ 65) were observed. There were no also statistically significant differences by sex for PPR. For clinical characteristics, there were no statistically significant differences by length of stay, ICU days, Case Mix Index or the presence of a mental health diagnosis for PPR.

30-day PPR was statistically different across ethnic groups (p=0.02); individuals documented with Native Hawaiian ethnicity had higher rates of 30-day PPR. A statistically significant difference was also seen in 30-day PPR by insurance type (p<0.001). Those with public insurance (either Medicare or Medicaid) were more likely to have a 30-day PPR compared to those with private insurance. Individuals who had a surgical encounter at index hospitalization were significantly less likely to have a 30-day PPR compared to those who did not have a surgical encounter at index hospitalization (p=0.002). Individuals who had a device to assist with mobility at index admission were also more likely to have a 30-day PPR (p<0.001). Individuals who came to the hospital through the emergency department at index admission were more likely to have a 30-day PPR compared to individuals who were admitted at index admission via Physician Referral (p<0.001). Individuals who were discharged at index admission to skilled nursing (SNF) or long-term care (LTC) facilities were also more likely to have a 30-day PPR compared to individuals who were discharged home to self-care at index admission (p=<0.001). Elixhauser comorbidity categories also showed statistical significance. Individuals with higher comorbidity were more likely to have a 30-day PPR, particularly those with >10 comorbid conditions (p<0.001).

Multivariable Model

In the multivariable model predicting 30-day PPR (Table 2), neither the variable for "lives alone" (OR: 1.15, 95% CI: 0.94-1.39) nor homelessness (OR: 0.87; 95% CI: 0.71-1.07) was a statistically significant predictor of 30-day PPR. Race and Surgical Encounter (Yes/No) were also not statistically significant variables.

Factors significantly associated with 30-day PPR were index admission source (specifically, those with physician referral were less likely to have a 30 day PPR compared to those admitted through the emergency department (OR: 0.73, 95% CI: 0.58-0.92)); use of a device for mobility-assistance at index admission (specifically, those with a device were less likely (OR: 0.72, 95% CI: 0.62-0.84)); Elixhauser Comorbidity score at index admission (specifically, those with 10+comorbidities were more likely (OR: 9.30, 95% CI: 4.30-20.00)); and discharge disposition at index admission (specifically, those with admitted to SNF were less likely compared to those who were discharged to home or self-care (OR: 0.65, 95% CI: 0.51-0.82)).

Table 4.1: Descriptive Statistics for patients with and without 30-day PPR following and Index Hospitalization (N=21,124) from two urban hospitals in Hawai‘i

Variables	All Patients (n=21,274)					
	No PPR	Have PPR	P-Value	Crude Odds Ratio	95% Confidence Interval	
Lives Alone			0.09			
Yes	3,376 (93.3%)	128 (3.7%)		0.84	0.70	1.02
No	16,981 (95.7%)	766 (4.3%)		Ref		
Homeless			0.01			
Yes	2,259 (94.7%)	126 (5.3%)		1.31	1.08	1.59
No	18,111 (95.9%)	771 (4.1%)		Ref		
Age Group			0.13			
≥65	11,496 (95.6%)	529 (4.4%)		1.11	0.97	1.27
<65	8,881 (96.0%)	368 (4.0%)		Ref		
Sex			0.40			
Male	10,611 (95.7%)	480 (4.3%)		1.06	0.93	1.21
Female	9,762 (95.9%)	417 (4.1%)		Ref		
Race			0.02			
Chinese	917 (95.5%)	43 (4.5%)		1.20	0.86	1.69
Filipino	3,316 (95.9%)	143 (4.1%)		1.11	0.89	1.38
Hawaiian	2,737 (94.5%)	160 (5.5%)		1.48	1.20	1.83
Japanese	5,204 (96.1%)	214 (3.9%)		1.06	0.87	1.30
OPI	1,353 (95.4%)	65 (4.6%)		1.16	0.88	1.52
Other	1,715 (95.9%)	74 (4.1%)		1.23	0.93	1.64
Caucasian	5,133 (96.2%)	200 (3.8%)		Ref		
Insurance			<0.001			
Public	13,241 (95.5%)	618 (4.5%)		1.66	1.42	1.94
Other	232 (94.3%)	14 (5.7%)		0.54	0.20	1.45

Private	6,902 (96.3%)	266 (3.7%)		Ref		
Admission Source			<0.001			
Referral	3,743 (97.1%)	110 (2.9%)		0.68	0.50	0.92
Transfer	1,521 (95.8%)	67 (4.2%)		1.10	0.85	1.42
Emergency	15,097 (95.4%)	721 (4.6%)		Ref		
Length of Stay	5.5±6.6	7.0±6.7	0.99	1.02	1.01	1.03
ICU Days[2]	0.4±1.7	0.5±1.8	0.99	1.03	0.99	1.06
Case Mix Index	1.9±1.4	1.9±1.4	0.99	1.02	0.97	1.06
Surgery			0.002			
Yes	7,255 (96.3%)	275 (3.7%)		0.80	0.69	0.92
No	13,120 (95.5%)	624 (4.5%)		Ref		
Device[3]			<0.001			
Yes	11,453 (96.9%)	372 (3.1%)		1.83	1.59	2.09
No	8,876 (94.4%)	524 (5.6%)		Ref		
Comorbidities			<0.001			
1-3	6,668 (97.7%)	156 (2.3%)		2.83	1.32	6.06
4-6	6,206 (96.4%)	234 (3.6%)		4.57	2.15	9.71
7-9	3,850 (94.5%)	225 (5.5%)		7.08	3.32	15.07
10+	2,805 (91.1%)	275 (8.9%)		11.87	5.59	25.23
0	848 (99.2%)	7 (0.8%)		Ref		
Mental Health			0.38			
Yes	14,797 (95.8%)	641 (4.2%)		1.07	0.92	1.24
No	5,578 (95.6%)	258 (4.4%)		Ref		
Discharged To			<0.001			
Hospice	498 (99.8%)	1 (0.2%)		0.05	0.00	0.33
SNF	2,347 (96.1%)	94 (3.9%)		0.92	0.74	1.15
Other Facility	2,639 (94.5%)	154 (5.5%)		1.36	1.14	1.63
Home	14,891 (95.8%)	650 (4.2%)		Ref		

[2] ICU Days = Time spent in the “Intensive Care Unit”
[3] Whether individuals require a device to aid with mobility (e.g., Wheelchair Cane, Walker, etc).

Table 4.2: Multivariable Logistical Model Predicting Having a 30-day PPR following an Index Hospitalization (n=21,124) from two urban hospitals in Hawai‘i

Variables		All Patients		
		OR	95% CI	
Lives Alone	Lives Alone	1.17	0.96	1.42
	Lives with Others	Reference		
Homeless	Yes	0.87	0.71	1.07
	No	Reference		
Admission Source	Referral	0.73	0.58	0.92
	Transfer	1.04	0.80	1.36
	Emergency	Reference		
Sex	Male	0.93	0.81	1.07
	Female	Reference		
Age	≥65	1.13	0.96	1.32
	<65	Reference		
Race	Chinese	1.14	0.81	1.60
	Filipino	0.95	0.76	1.18
	Hawai‘ian	1.12	0.90	1.40
	Japanese	1.01	0.82	1.23
	OPI	0.94	0.70	1.26
	Other	1.12	0.85	1.48
	Caucasian			
Surgery	Yes	0.94	0.80	1.11
	No	Reference		
Payer	Public	1.29	1.09	1.53
	Other	0.61	0.22	1.66
	Private	Reference		
Device	Yes	0.72	0.62	0.84
	No	Reference		
Comorbidities	1-3	2.67	1.24	5.72
	4-6	3.98	1.86	8.51
	7-9	5.91	2.75	12.70
	10+	9.30	4.30	20.00
	0	Reference		
Discharged to	Hospice	0.03	0.00	0.21
	SNF	0.65	0.51	0.82
	Other Facility	1.10	0.91	1.33
	Home	Reference		

Discussion

Despite overwhelming evidence that social factors are critical determinants of health, they are rarely captured in health system EHRs in a routine manner (Matthews, Alder, Forrest, and Stead, 2016). Several major entities, including the Institute of Medicine and Centers for Medicare and Medicaid Services, are calling for clinical and public health practitioners to continue to examining ways to effectively collect these social and behavioral domains, particularly in acute care settings (IOM, 2014). Both the methods of collecting this data and the findings from this research add useful new evidence to the growing literature about how to effectively capture these social factors as a part of routine clinical care.

Living alone, routinely collected in inpatient clinical care in this hospital system with standardized protocols, and homelessness, identified from free text searches, were relatively common in this inpatient sample. Almost 20% of the sample lived alone and over 10% were documented as homeless. Homelessness predicted PPR in descriptive analyses, though neither of these social factors predicted PPR once other factors were controlled. Instead, indicators of physical frailty and greater illness were significant. This is congruent with a vast body of evidence that has identified the importance of comorbidity in predicting PPR, even to the exclusion of other common social factors that commonly predict health disparities, particularly race/ethnicity (Sentell et al, 2016; Nakagawa, Ahn, Taira, Miyamura, and Sentell, 2016).

Both these social domains (isolation and homelessness) may have some challenges in practicality of data collection. Social isolation is complex and difficult to define (Bucholz, and Krumholz, 2012). Accordingly, it is a difficult concept to operationalize within the EHR. Comprehensively measuring social relationships requires "consideration of both structural (e.g., marital status, and living arrangements) and functional (e.g., emotional and perceived) aspects" of isolation or the quantity and quality of relationships (Reeves, Prager, Fang, Stamplecoski, and Kapral, 2014; Friedler, Crapser, and McCullough, 2015). More complex conceptual models of social isolation posit that four different levels should be measured to get an adequate picture, including loneliness, social support, social network, and social capital (Wang, et al, 2017). IOM's best practice recommendations for capturing social isolation in the electronic medical record is the Berkman-Syme Social Network Index (SNI), comprised of four components: marriage or partnership, frequency of contact with friends and family, frequency of religious

participation, and group membership (Behforouz, Drain, Rhatigan, 2014). A systematic overview literature on social isolation from 2000-2017 conducted by Leigh-Hunt et al (2017) identified 62 different measurement scales used for social isolation among 40 studies. Moreover, many clinicians may hesitate to ask questions that feel private in nature if they are not directly related to immediate clinical or diagnostic needs of the patient (Hripcsak et al, 2015; Nakagawa et al, 2016). This limits the amount social isolation measures available to feasibly include in EHRs, the data source for the majority of the research on healthcare utilization. Despite recognized limitations, living alone is a commonly used proxy for social isolation because of its ease of data collection (Reeves et al, 2014; Holt-Lunstad, Smith, and Layton, 2010).

For the Hawai‘i health care system used in this study, the measure of whether individuals "lived alone" was consistently documented and frequently referenced by frontline clinicians to determine whether additional post-discharge care would be required for patients (e.g., identification of caregivers, higher frequency of post-discharge phone calls, etc.). This study helped to determine whether this simple proxy was a predictive of 30-day PPR. For these two hospital facilities, the identification of individuals who "live alone" was not a predictor of 30-day PPR. This could indicate that individuals in the "lives alone" cohort may have some protective factors. For example, it may be an indicator of an individual's level of independence. Another (positive) reason the data did not align with our hypothesis may be that providers are using this flag effectively to pre-emptively provide individuals who are "living alone" with heightened-levels post-discharge care.

Several regionally-relevant factors may also explain why social isolation was not a significant predictor of 30-day PPR. First, the state of Hawai‘i has the highest national percent of multigenerational households, accounting for 11.1% of all family households in the state (Lofquist, 2012). This could be due to cultural or economic reasons (e.g., high-cost of living; 27). Accordingly, this dataset may have a smaller sample of individuals living alone compared to other areas in the United States. "Living Alone" within the state of Hawai‘i may thus be an indicator of certain protective factors, such as higher income.

A second factor unique to this dataset is a discharge-planning bill (Hawai‘i State Legislature, 2016) that was passed through the Hawai‘i state legislature in March 2016 (during the course of this data collection). This bill requires hospitals to adopt and maintain discharge

policies consistent with federal regulations and asks providers to identify and document a designated caregiver for each patient prior to discharge. It is possible that "identification of a designated caregiver" has improved readmission outcomes, particularly among individuals who live alone.

Although homelessness was a statistically significant predictor of readmissions in crude analyses, it was not statistically significant once other control variables were added. For this variable, this hospital system created a wild card search for "*homeless*" in free-text fields related to "residence." This method of documenting homelessness is likely to significantly underestimate homelessness and introduces classical measurement error leading to attenuation bias, making it harder to detect an effect. For example, the logic does not capture individuals who provide a homeless shelter for their residential address. Similarly, it does not address those with unstable housing situations (such as living on a friends' couch), who may also be vulnerable to readmissions.

Individuals experiencing homelessness are expected to have higher readmissions for a variety reasons, including higher comorbidity rates associated with inadequate living conditions and limited access to primary care (Saab et al, 2016). In this study, the percent of homeless individuals with high comorbidity counts was significantly higher than their peers ($p<0.001$; see figure 2). It is possible that the strength of the relationship between comorbidity and readmissions masked the effect of homelessness in the multivariate models. Future research could use mediation analyses to better disentangle the causal relationship between homelessness, comorbidities, and readmissions.

Whether an individual had a device to assist with mobility (y/n) was statistically significant in both the descriptive statistics and multivariable analyses. "Level of mobility" is another Social and Behavioral Domain (SBD) that the IOM recommends should be captured in a standard way in the EHR (IOM, 2014). Interestingly, they focus their recommended measures on leisure physical activity. While such measurements are of interest for the outpatient settings and/or younger populations, they may not be suitable for hospital settings or geriatric populations. Further consideration should be given to identify standard ways to measure physical activity or activities of daily living for these higher acuity groups.

Limitations

This data is limited to the frequency of 30-day PPR within one hospital system in Hawai‘i, which may limit generalizability. It may also under-report the true frequency of 30-day PPR per patients, particularly for individuals with subsequent hospital encounters at other healthcare systems. Our measures may not have fully operationalized our constructs. Other potential confounding variables for which we lack data include preferred language, compliance to post-discharge medication, and income. Individuals with lower income could lack resources to pay for housing, leading to homelessness, and lower incomes could indirectly be associated with the necessary resources to pay for preventive services, which in turn lead to hospital readmissions. Thus, the effect of homelessness on readmissions may still be larger in magnitude (though statistically insignificant) given that we did not control for income.

Conclusions and Future Research Implications:

Given that our independent variable of "lives alone" did not appear to have predictive value for all-cause 30-day PPR, modifying the granularity of social isolation measures could be a fruitful area of future study. While identification of "living alone" has been found to be predictive of both morbidity and mortality, it does not provide the same granularity of whether the patient "perceives loneliness" in addition to living alone (Valtorta, 2018; Holt-Lunstad et al, 2010). Further research is needed to understand how to best operationalize more robust social measures, including social isolation, in the acute care setting.

There are similar limitations to capturing homelessness in the EHR. Free text capture of homelessness underreports those who are unstably housed or those who are currently living in shelters. While IOM has recommendations to capture residential address and median census tract income, there are no clear recommendations around how this vulnerable population should be handled (IOM, 2014). The current literature notes limitations and mixed approaches currently used to capture homelessness in the EHR, ranging from listing of a shelter address to the number of home address changes as a proxy of "unstably housed" (Doran et al, 2013). A study by Doran et al suggests that homelessness screening should be completed by multiple practitioners to ensure redundancy and increase capture rates (2013). Identifying and implementing standard approaches to capturing homelessness in the EHR is critical to for health policy and programming.

Because social and behavioral factors impact patient health, health care systems must rethink the way these measures are defined and captured in the EHR (Beforouz et al, 2014). This study illustrates how social factors (i.e., homelessness and social isolation) can be leveraged for predictive modeling of acute care outcomes. Further research is needed to refine and operationalize social and behavioral domains in a discrete way that can be practically collected in care, specifically for acute care populations.

5. CONCLUSION

Summary of Findings

These three studies contribute critical new information to the overarching conversation around how to effectively document SBD measures in the EHR. While there are many efforts to implement these measures in primary care settings, there is less research on the feasibility of including these measures in acute care settings. Capturing SBD in acute care settings is critical because vulnerable populations are more likely to visit the emergency department for primary care and/or be hospitalized from lack of primary care. This dissertation demonstrates that SBD can be incorporated in to acute care quality efforts and social service referrals, subsequently providing improvement to patients' immediate course of care. However, we must continue to examine the feasibility of implementing these measures within the nuances of various acute care workflows. Identifying creative ways to capture SBD, such as patient self-report or natural language processing, may be more optimal mechanisms to obtain trended SBD data with minimal disruptions to clinical workflows.

In Study 1, focus groups were conducted with nurses and case managers from acute-care settings to understand the barriers and facilitators to documenting SBD in the EHR. Participants identified time, mandated reporting, detrimental patient implications, and data integrity as barriers to capturing SBD in the EHR. The participants felt that alternate methods of reporting and closed feedback loops would facilitate SBD data capture in the EHR. Studies Two and Three provided different examples of how to evaluate SBD captured within the EHR against common acute care outcomes.

In Study 2, case-mix adjusted average length of stay (CMI-Adjusted ALOS) was evaluated at two hospital sites: one where standardized mobility measures were implemented and a control site (where the mobility measures are not routinely captured). The results of this study did not result in a statistically significant difference in CMI-Adjusted ALOS at the case site. This study was consistent not with previous studies showing that mobility promotion can reduce length of stay (Hoyer, 2016). However, it did demonstrate that iterative quality improvement efforts may be one adoption mechanism for SBD measures in the EHR.

In Study 3, social isolation (as measured by whether patients "live alone") and homelessness were measured against potentially preventable readmission. These variables were

not significant in the multivariable model after adding the Elixhauser Comorbidity data. Two regionally specific factors, including a high percent of multi-generational homes and local law that requires hospitals to identify, educate, and document care-givers upon admission may influence the findings from this study. This study highlights the need for continued refinement of SBD measures and importance of understanding the regionally-specific factors that may contribute to SBD outcomes.

Implications for Policy and Practice

In the qualitative study (Study 1), providers expressed concern about asking patients sensitive social and behavioral questions without the intent to address the issue personally or without adequate referral resources. The quantitative findings in this dissertation demonstrated that acute care providers will consistently document SBD domains if the measurements have a direct impact on patient care. In Study 2, documenting mobility fields in the EHR allowed other care members to see what physical activity had been completed with the patient during the hospital stay and use the information accordingly (e.g., a nurse understands the patient's current functional status, the physical therapist could offer more or less vigorous exercises depending on the patient's progression over the last few days, case managers can identify whether an assistive mobility device needed to be ordered for the patient prior to discharge, etc). In Study 3, social isolation measures were added to ensure that patients had a care-giver post-discharge. If no care-giver could be identified, alternatives (such as a home health service) were considered to ensure the patient had a safe discharge and to reduce the likelihood of an unnecessary readmission. Collectively, these studies point to a critical consideration for policy and practice: in order for providers to be comfortable with SBD screening, there needs to be a clear and understood purpose.

Also, this dissertation suggests that in order to effectively introduce a SBD domain into a health-system's electronic health record, that change must be accompanied by 1) education to the provider to explain why the measure is being captured, and 2) a clear pathway to resources for the patient should a social need be identified through screening. These findings are consistent with previous articles on the subject, several of which claim it is unethical to ask providers to screen for social resources when the adequate community resources are not available (Palacio, Suarez, Tamariz, and Seo, 2018; Garg, A., Boynton-Jarrett, R., & Dworkin, P. H., 2016). Accordingly, considerable caution should be taken as the 12 IOM SBD measures are added to

health care systems' EHR to ensure that effective infrastructure is in place to support each of the identified social needs.

Not every health care system will have adequate resources or partnerships in place to support all 12 of the IOM domains. Accordingly, the major implication for practice is that every health care organization must critically assess the 12 IOM SBD domains and ask whether there are resources to respond to a social need when and if it is identified. Even assuming the infrastructure is available, the health care system must consider how they will educate their staff about the why the screening is being completed and what resources are available when a patient screens positively for a social need. Health care systems may need to choose to roll out SBD domains in a piece-meal fashion (when there is organizational justification and community readiness to support the measures).

From a policy standpoint, local governments need to partner with health care systems in several ways collectively support SBD needs in the community. If there are tight partnerships between health care facilities and the local government, SBD data can be used to inform community need and guide policy decisions. However, in order to enable the capture of SBD, health care providers need to be aware of the community resources that are available to them. During the qualitative study (Study 1), one participant recommended that the local government provide hospitals with an up-to-date list of the certified non-profit organizations categorized by which "social need" the non-profit addresses, in order to facilitate easier referrals. Methods to enable this workflow are both important and likely to bring new challenges and time commitments. Another concern expressed in the qualitative study (Study 1) was that after a non-profit organization is identified and trusted, the funding is not reliable year-over-year. Tighter partnerships between government and health care systems (specifically forums that provide feedback about which community resources are critical to supporting the social needs identified by health care providers) may help ensure that trusted community resources maintain adequate funding.

Future Research

This dissertation identifies a number of important questions for future research. First, more research is needed on how to tie SBD to acute care outcomes in order to incentivize the adoption of these measures. This dissertation examined SBD against outcomes including CMI-Adjusted ALOS and Potentially Preventable Readmission, but a more meaningful measure may

be “number of referrals to the appropriate resource” over time. Showing that screening for SBD helped ensure that patients’ needs are being met (either inside or outside) of the hospital, seemed to be of critical importance to the providers in Study 1. This also brings to light the continued need for feasibility research around how to make this data more interoperable, meaning a physician can refer a patient to a community resource and can receive feedback that the referral was completed.

Another critical area of research that was not addressed in this dissertation is patient’s thoughts or expectations around how and when they would like to be asked about SBD, especially in the acute care setting. Future research should elicit feedback from patients – particularly individuals that the need for additional social resources—to understand how these SBD measures could be implemented in a way that leads to a positive patient experience.

The results from this dissertation demonstrate that SBD can be incorporated in to the EHR, as long as the appropriate referral resources are made available to the provider or the SBD measure has some immediate impact to course of care. However, we must continue to examine the feasibility of implementing these measures within the nuances of various acute care workflows (for example, even within hospital settings, where and how SBD is captured may differ depending on whether a patient is visiting the ED or the OR). Identifying creative ways to capture SBD, such as patient self-report or natural language processing, may be more optimal mechanisms to obtain trended SBD data, with minimal disruptions to clinical workflows.

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APPENDIX 1: IRB APPROVAL | STUDY 1

WIRB
A WIRB-Copernicus Group Company

Certificate of Action

Investigator Name: Emiline LaWall, MS	**Board Action Date:** 04/06/2018
Investigator Address: 55 Merchant Street, 26th Floor Honolulu, HI 96813, United States	**Approval Expires:** 04/06/2019 **Continuing Review Frequency:** Annually
Sponsor: Emiline LaWall, MS **Institution Tracking Number:**	**Sponsor Protocol Number:** 2018-019-2018-019 **Amended Sponsor Protocol Number:**
Study Number: 1184638	**IRB Tracking Number:** 20180703
Work Order Number: 1-1071541-1	**Panel:** 2
Protocol Title: Social Behavioral Determinants in the Acute Care Electronic Health Records (Barriers and Facilitators for Adoption of Social and Behavioral Determinants)	

THE FOLLOWING ITEMS ARE APPROVED:
Investigator
Focus Group Questions #17524950.0 - As Submitted
Protocol (10-15-2017)
Consent Information Sheet [IN0]
Intro Script #17546746.0 - As Submitted

Please note the following information:
The Board requires that all subjects must be able to consent for themselves to be enrolled in this study. This means that you cannot enroll incapable subjects who require enrollment by consent of a legally authorized representative.

The Board found that this research meets the requirements for a waiver of documentation of consent under 45 CFR 46.117(c)(2)

THE IRB HAS APPROVED THE FOLLOWING LOCATIONS TO BE USED IN THE RESEARCH:
Pali Momi Medical Center, 98-1079 Moanalua Road, Aiea, Hawaii 96701
Straub Medical Center, 888 S. King Street, Honolulu, Hawaii 96813

ALL IRB APPROVED INVESTIGATORS MUST COMPLY WITH THE FOLLOWING:
As a requirement of IRB approval, the investigators conducting this research will:

- Comply with all requirements and determinations of the IRB.
- Protect the rights, safety, and welfare of subjects involved in the research.
- Personally conduct or supervise the research.
- Conduct the research in accordance with the relevant current protocol approved by the IRB.
- Ensure that there are adequate resources to carry out the research safely.
- Ensure that research staff are qualified to perform procedures and duties assigned to them during the research.
- Submit proposed modifications to the IRB prior to their implementation.
  - Not make modifications to the research without prior IRB review and approval unless necessary to eliminate apparent immediate hazards to subjects.
- Submit continuing review reports when requested by the IRB.
- Submit a closure form to close research (end the IRB's oversight) when:
  - The protocol is permanently closed to enrollment
  - All subjects have completed all protocol related interventions and interactions
  - For research subject to federal oversight other than FDA:
- No additional identifiable private information about the subjects is being obtained
- Analysis of private identifiable information is completed

This is to certify that the information contained herein is true and correct as reflected in the records of this IRB. WE CERTIFY THAT THIS IRB IS IN FULL COMPLIANCE WITH GOOD CLINICAL PRACTICES AS DEFINED UNDER THE U.S. FOOD AND DRUG ADMINISTRATION (FDA) REGULATIONS, U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES (HHS) REGULATIONS, AND THE INTERNATIONAL CONFERENCE ON HARMONISATION (ICH) GUIDELINES.

Full Accreditation

Board Action: 04/06/2018

- If research approval expires, stop all research activities and immediately contact the IRB.
- Promptly report to the IRB the information items listed in the IRB's "Prompt Reporting Requirements" available on the IRB's Web site.
- Not accept or provide payments to professionals in exchange for referrals of potential subjects ("finder's fees.")
- Not accept payments designed to accelerate recruitment that are tied to the rate or timing of enrollment ("bonus payments") without prior IRB approval.
- When required by the IRB ensure that consent, permission, and assent are obtained and documented in accordance with the relevant current protocol as approved by the IRB.
- Promptly notify the IRB of any change to information provided on your initial submission form.

Consistent with AAHRPP's requirements in connection with its accreditation of IRBs, the individual and/or organization shall promptly communicate or provide, the following information relevant to the protection of human subjects to the IRB in a timely manner:

- Upon request of the IRB, a copy of the written plan between sponsor or CRO and site that addresses whether expenses for medical care incurred by human subject research subjects who experience research related injury will be reimbursed, and if so, who is responsible in order to determine consistency with the language in the consent document.
- Any site monitoring report that directly and materially affects subject safety or their willingness to continue participation. Such reports will be provided to the IRB within 5 days.
- Reports from any data monitoring committee, data and safety monitoring board, or data and safety monitoring committee in accordance with the time frame specified in the research protocol.
- Any findings from a closed research when those findings materially affect the safety and medical care of past subjects. Findings will be reported for 2 years after the closure of the research.

If your research site is a HIPAA covered entity, the HIPAA Privacy Rule requires you to obtain written authorization from each research subject for any use or disclosure of protected health information for research. If your IRB-approved consent form does not include such HIPAA authorization language, the HIPAA Privacy Rule requires you to have each research subject sign a separate authorization agreement. "

Federal regulations require that the IRB conduct continuing review of approved research. You will receive Continuing Review Report forms from this IRB when the expiration date is approaching.
Thank you for using this WCG IRB to provide oversight for your research project.
DISTRIBUTION OF COPIES:
Contact, Company
Andrea Siu, MPH, Hawaii Pacific Health
HPH Research Institute, Hawaii Pacific Health
Emiline LaWall, MS, Hawaii Pacific Health

COA Template 01-03-2016

APPENDIX 2: WAIVER OF CONSENT

Research Subject Information Sheet

TITLE: Social Behavioral Determinants in the Acute Care Electronic Health Records

(Barriers and Facilitators for Adoption of Social and Behavioral Determinants)

PROTOCOL NO.: 2018-019-2018-019

WIRB® Protocol #20180703

SPONSOR: Emiline LaWall, MS

INVESTIGATOR: Emiline LaWall, MS
55 Merchant Street

26th Floor

Honolulu, Hawaii 96813

United States

STUDY-RELATED PHONE NUMBER(S): Emiline LaWall, MS

808-535-7394

You are being asked to be in a research study that will try to examine barriers and facilitators to documenting social and behavioral determinants (i.e., population health measures) within the electronic health record (Epic).

Your participation will involve participating in a focus group with 3-7 of your co-workers and take about 60 to 90 minutes. Please note, these focus groups are anonymous but they will be audio-recorded for further analysis. We will be conducting 4-6 focus groups in total.

There are no known risks associated with being in this research.

You may not receive a direct benefit if you agree to participate. However, people in the future may benefit from the information obtained from this research and it will serve to advance our understanding of population health analytics.

You may choose to not participate in this study. Alternatively, you may leave the focus group at any point in time.

You will not be paid for your participation in this focus group.

Contact Emiline LaWall at 808- 535-7394 for questions, concerns or complaints about the research or if you think you have been harmed as a result of joining this research. Contact the Western Institutional Review Board (WIRB) if you have questions about your rights as a research subject, concerns, complaints or input: 1-800-562-4789. WIRB is a group of people who perform independent review of research.

The study staff will share the records generated from this research with the sponsor, regulatory agencies such as the IRB. To protect confidentiality, names will not be collected as a part of this study. If the results of this research are published, your identity will remain confidential. This information is shared so the research can be conducted and properly monitored. The people receiving this information may not be required to protect it and your information may be redisclosed without your permission. If you do not provide permission to use your information you cannot be in the study.

APPENDIX 3: FOCUS GROUP INTRODUCTION SCRIPT

Hello, my name is Emiline LaWall. I am currently a Project Manager with Hawai‘i Pacific Health and may have worked with you in some capacity.

I am also a graduate student at the University of Hawai‘i at Mānoa pursuing my doctorate in Public Health. As part my dissertation, I am completing a research on how Social and Behavioral Determinants (SBD) of health are integrated into the Electronic Health Record (EHR).

Among other things, documentation of SBD in the EHR has been shown to:

- Improve Real-Time Risk-Stratification for Vulnerable Populations
- Increase Referrals to Social and Community Services
- Provide Actionable Data for Population Health Interventions

However, I know there are some clinical and administrative challenges to making some of these changes, for example:

- Competing priorities, especially with urgent/emergent cases
- Documentation fatigue
- Sensitivity to screening for psychological or social issues as a clinical providers.

I am asking you to participate in this study because you either: a) use the EHR routinely throughout your work day or b) are involved in the process of adding metrics to the EHR.

Please know that I am conducting these focus groups as an academic researcher, not as an IT Project Manager. Feedback that is both in favor or in opposition of adding Social and Behavioral Domains to the EHR serve as valuable findings. Information you shared will remain anonymous in my final write-up. Before we begin, please take a few minutes at this time to review the “Research Subject Information Sheet” provided to you.

APPENDIX 4: FOCUS GROUP QUESTIONS

1. With each patient admission, nurses collect a free-text "social history" of the patient. What information is typically collected in this social history? What (if any) of this information is useful to you in your current role? Please describe how the information is used.

2. Are there any aspects of an individual's "Social History" that you wish were available discretely for reporting or screening purposes? If so, what would those elements be? How would you use them in your day-to-day work?

3. Examine the list of Social Behavioral Domains from the Institute of Medicine's (IOM) Recommendations. How do these recommendations compare to information your currently collect?

4. Do any of the IOM recommendations stand out to you as being particularly meaningful or particularly meaningless? If so, please describe which ones and why?

5. If you were to implement these recommendations, which domain(s) would you implement first? Who would be responsible for collecting the information? When would it be collected?

6. What would be some of the barriers to implementing these measures in the inpatient setting?

7. What would be some of the facilitators to implementing these measures in the inpatient setting?

8. If you had access to the information from the IOM recommendations, how would you use it?

9. Is there anything missing from these IOM recommendations (e.g., Homelessness, caregiver dynamics, etc)? What is missing and why is it important? How would you recommend implementing these measures?

APPENDIX 5: IRB APPROVAL | STUDIES 2 & 3

HAWAIʻI PACIFIC HEALTH | KAPIʻOLANI PALI MOMI STRAUB WILCOX

November 7, 2017

Emiline LaWall
Hawaiʻi Pacific Health
55 Merchant Street, 26th Floor
Honolulu, HI 96813

Dear Ms. LaWall:

SUBJECT: EXEMPT FROM REGULATIONS
Principal Investigator: Emiline LaWall
Project Title: Social Behavioral Determinants in the Acute Care Electronic Health Records
HPHRI Study Number: 2017-138

On November 6, 2017November 7, 2017 a designee of the Institutional Official of Hawaiʻi Pacific Health determined the above referenced study to be exempt from regulations using the guidelines set by the Office of Human Research Protection (45 CFR 46), because your study does not meet the criteria for human subject research.

As the principal investigator you are required to submit any changes to the protocol, including closure of the study, and a progress report to Hawaiʻi Pacific Health Research Institute as requested.

Hawaiʻi Pacific Health Research Institute will maintain files on all studies determined to be exempt from regulations.

Sincerely,

David T. Horio, MD
Hawaiʻi Pacific Health Institutional Official Designee

DH/as

APPENDIX 6: STRATIFIED ANALYSES FOR STUDY 3

Demographic Characteristics for Individuals who "Live with Others" compared to those who "Live Alone" (with/without a Potentially Preventable Readmission).

	All Patients (n=21,274)			Individuals "Living with Others" (n=17,767)			Individuals "Living Alone" (n=3,507)		
	No PPR	Have PPR	P-Value	No PPR	Have PPR	P-Value	No PPR	Have PPR	P-Value
Number of Patients	20,375	899		16,995	772		3,380	127	
Age Group			0.2689			0.1025			0.3461
<65	9,312 (45.7%)	394 (43.8%)		7,884 (46.4%)	335 (43.4%)		1,428 (42.3%)	59 (46.5%)	
≥65	11,063 (54.3%)	505 (56.1%)		9,111 (53.6%)	437 (56.6%)		1,952 (57.7%)	68 (53.54%)	
Sex			0.4402			0.3585			0.8571
Male	10,611 (52.1%)	480 (53.4%)		8,827 (51.9%)	358 (46.4%)		1,784 (52.8%)	66 (51.97%)	
Female	9,762 (47.9%)	419 (46.6%)		8,168 (48.1%)	414 (53.6%)		1,596 (47.2%)	61 (48.0%)	
Race			<0.05			0.107			<0.05
Caucasian	5,133 (21.2%)	200 (22.3%)		3,917 (23.0%)	156 (20.2%)		1,216 (36.0%)	44 (34.7%)	
Chinese	917 (4.5%)	43 (4.8%)		746 (4.4%)	39 (5.1%)		171 (5.1%)	4 (3.2%)	
Filipino	3,316 (16.3%)	143 (15.9%)		3,037 (17.9%)	137 (17.8%)		279 (8.3%)	6 (4.7%)	
Hawaiian	2,737 (13.4%)	160 (17.8%)		2,373 (14.0%)	134 (17.4%)		364 (10.8%)	26 (20.5%)	
Japanese	5,204 (25.5%)	214 (23.8%)		4,320 (25.4%)	183 (23.7%)		884 (26.2%)	31 (24.4%)	
OPI	1,353 (6.6%)	65 (7.23%)		1,293 (7.6%)	61 (7.9%)		60 (1.8%)	3 (2.4%)	
Other	1,715 (8.4%)	74 (8.23%)		1,309 (7.7%)	62 (8.0%		406 (12.0%)	13 (10.2%)	
Insurance			<0.05			0.3369			0.0590
Private	6,902 (33.9%)	266 (29.6%)		6,009 (35.2%)	222 (32.7%)		887 (27.0%)	43 (19.8%)	
Public	13,241 (65.0%)	618 (68.85%)		10,881 (63.8%)	448 (66.0%)		2,347 (71.4%0	169 (77.9%)	
Other	232 (1.14%)	14 (1.6%)		178 (1.0%)	9 (1.3%)		54 (1.6%)	5 (2.3%)	
Homeless			<0.05			<0.01			0.5239
Yes	2,259 (11.1%)	126 (14.0%)		1,838 (10.8%)	108 (14.1%)		408 (12.1%)	18 (14.0%)	
No	18,111 (88.9%)	771 (86.0%)		15,136 (89.2%)	658 (85.9%)		2,968 (87.9%)	111 (86.1%)	

Clinical Characteristics for those "Live with Others" compared to those who "Live Alone" (with/without a Potentially Preventable Readmission).

	All Patients | (n=21,274)			Individuals "Living with Others" | (n=17,767)			Individuals "Living Alone" | (n=3,507)		
	No PPR	Have PPR	P-Value	No PPR	Have PPR	P-Value	No PPR	Have PPR	P-Value
Number of Patients	20,356	896		17,608	679		3,288	217	
Admission Source			<0.001			<0.001			0.8405
Emergency	15,097 (74.1%)	721 (80.2%)		12,503 (73.6%)	622 (80.6%)		2,594 (76.7%)	99 (78.0%)	
Referral	3,743 (19.4%)	110 (12.2%)		3,184 (18.7%)	92 (11.9%)		559 (16.5%)	18 (14.2%)	
Transfer	1,521 (7.5%)	67 (7.4%)		1,297 (7.6%)	57 (7.4%)		224 (6.6%)	10 (7.8%)	
Length of Stay	5.5±6.6	7.0±6.7	1.000	5.4±6.4	6.9±6.6	1.000	5.9±7.4	7.5±0.67	1.000
ICU Days[4]	0.4±1.7	0.5±1.8	1.000	0.4±1.7	0.5±1.9	1.000	0.3±1.6	0.4±1.1	1.000
Case Mix Index	1.9±1.4	1.9±1.4	1.000	1.9±1.4	1.9±1.4	1.000	1.9±1.4	1.7±1.2	1.000
Surgery			p<0.01			<0.05			<0.05
Yes	7,255 (35.6%)	275 (30.6%)		6,069 (35.7%)	243 (31.5%)		1,186 (35.1%)	32 (25.2%)	
No	13,120 (64.4%)	624 (69.4%)		10,926 (64.3%)	529 (68.5%)		2,194 (64.9%)	95 (74.8%)	
Device[5]			<0.001			<0.001			<0.001
Yes	11,453 (56.3%)	372 (41.5%)		7,433 (43.8%)	455 (59.2%)		2,443 (42.7%)	69 (54.3%)	
No	8,876 (43.7%)	524 (58.5%)		9,520 (56.2%)	314 (40.8%)		1,993 (57.3%)	58 (45.7%)	
Comorbidities			<0.001			<0.001			<0.001
0	848 (4.2%)	7 (0.8%)		712 (4.2%)	6 (0.8%)		135 (4.0%)	1 (0.8%)	
1-3	6,668 (32.7%)	156 (17.4%)		5,567 (32.8%)	133 (17.4%)		1,093 (32.4%)	22 (17.1%)	
4-6	6,206 (30.5%)	234 (26.1%)		5,100 (30.0%)	200 (26.1%)		1,098 (32.5%)	33 (25.6%)	
7-9	3,850 (18.9%)	225 (25.1%)		3,203 (18.9%)	185 (24.2%)		646 (19.1%)	40 (31.0%)	
10+	2,805 (13.8%)	275 (30.7%)		2,399 (14.1%)	242 (31.6%)		404 (12.0%)	33 (25.6%)	
Mental Health			0.3847			0.1687			0.5234
Yes	14,797 (72.6%)	641 (71.3%)		4,421 (26.0%)	218 (28.2%)		1,157 (34.3%)	40 (31.5%)	
No	5,578 (27.4%)	258 (29.70%)		12,574 (74.0%)	554 (71.8%)		2,223 (65.8%)	87 (68.5%)	
Discharged To			<0.001			<0.001			0.5118
Home	14,891 (73.1%)	650 (72.3%)		12,577 (74.0%)	559 (72.4%)		2,314 (68.5%)	91 (71.6%)	
Hospice	498 (2.4%)	1 (0.1%)		452 (2.7%)	1 (0.1%)		46 (1.4%)	0 (0.0%)	
SNF	2,347 (11.5%)	94 (10.5%)		1,792 (10.5%)	76 (9.8%)		555 (16.4%)	18 (14.2%)	
Other Facility	2,639 (13.0%)	154 (17.1%)		2,174 (12.8%)	136 (17.6%)		465 (13.4%)	17 (14.2%)	

[4] ICU Days = Time spend in the "Intensive Care Unit"

[5] Whether individuals require a device to aid with mobility (e.g., Wheelchair Cane, Walker, etc).